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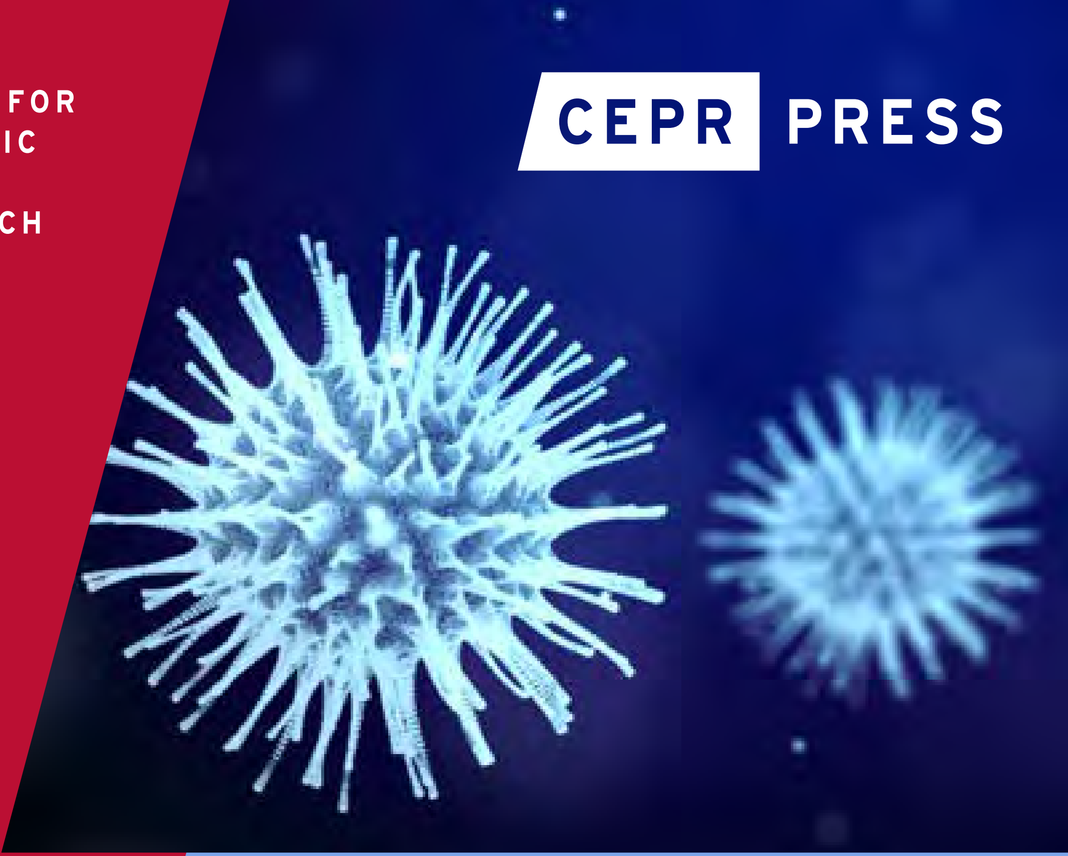

COVID ECONOMICS

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.

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Ethics

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
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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 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*.

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Pandemic Control in ECON-EPI Networks[1]

Marina Azzimonti[2], Alessandra Fogli[3], Fabrizio Perri[4] and Mark Ponder[5]

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We develop an ECON-EPI network model to evaluate policies designed to improve health and economic outcomes during a pandemic. Relative to the standard epidemiological SIR set-up, we explicitly model social contacts among individuals and allow for heterogeneity in their number and stability. In addition, we embed the network in a structural economic model describing how contacts generate economic activity. We calibrate it to the New York metro area during the 2020 COVID-19 crisis and show three main results. First, the ECON-EPI network implies patterns of infections that better match the data compared to the standard SIR. The switching during the early phase of the pandemic from unstable to stable contacts is crucial for this result. Second, the model suggests the design of smart policies that reduce infections and at the same time boost economic activity. Third, the model shows that re-opening sectors characterized by numerous and unstable contacts (such as large events or schools) too early leads to fast growth of infections.

1 We thank Maria Cristina De Nardi, as well participants at several seminars and conferences for great comments and suggestions. Also many thanks to Dhananjay Ghei and Thomas Gill for outstanding research assistance. The views expressed herein are those of the authors and not necessarily those of the Federal Reserve Bank of Minneapolis or the Federal Reserve System.
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1 Introduction

The COVID-19 pandemic of 2020 presents a formidable challenge to policymakers: for the first time in decades they face a trade-off between epidemiological costs (lives) and economic costs (livelihoods). The key question that motivates this paper is how to design *smart* policies which are effective in reducing the spread of the disease while at the same time minimizing economic costs.

Our point of departure is that the spread of infections and economic activity happen through the same network of human interactions. We develop an ECON-EPI network model of a city, characterized by three components. The first one is the network of human interactions that specifies contacts among individuals through different network layers. The second one is the ECON component, which describes how economic activity is created on the network. The last one is the EPI component, specifying how the disease spreads through individuals across the city.

When a pandemic hits, several links of the network are severed, either as a consequence of mitigation policies or because individuals change their behavior as a response. Our key insight is that the dynamic consequences, both in terms of infections and economic outcomes, strongly depend on the type of links that are severed. Cutting certain types of links has a large impact on infections and a relatively small economic cost, while cutting other types has only a marginal impact on the infection levels but large economic costs. We find that the ECON-EPI network constitutes a useful framework to understand and measure the epidemiological and economic costs of limiting different types of social interaction, and therefore it provides guidance in designing effective policies to control the pandemic while preserving economic activity.

We start by describing a multilayered network model, of the type commonly used in the epidemiological literature. Individuals in the network differ in several dimensions (such as age, family structure and work characteristics) and interact with each other through different network layers. These layers capture the main contexts of interaction among individuals in a city, such as homes, neighborhoods, schools, public transportation, stores, entertainment venues, and workplaces. These different social contexts are also often the target of actual mitigation policies aimed at limiting the extent of interaction allowed (such as the closure of schools, the limits on large gatherings, or the shut down of non-essential businesses). Some layers (such as family and neighborhood) feature frequent and repeated interactions among a small set of individuals. Other layers (such as public transportation or shopping venues) feature less frequent and more randomized contacts among a larger set of individuals. These differences play a critical role in the speed of diffusion of the disease throughout the city, more numerous and random contacts leading to faster spreading.

Next we introduce the EPI component, which describes the dynamics of the disease. We model the progression of the disease as in the standard Susceptible-Infected-Recovered (SIR) model, while allowing for heterogeneity among infected individuals in the manifestation of symptoms and in the transmissibility upon contact. If we interpret the individuals in the economy as nodes in the network, we can express the key difference between the standard SIR set-up and our network model in terms of the infection probability of susceptible nodes. In the SIR set-up, this probability is the same for all nodes and depends on the average number of infected nodes in the system. In the network set-up, it differs across nodes, and for each node it depends on its own fraction of infected connections. This difference is crucial to understand why the SIR and the network model generate very different infection dynamics.

The last component of the network model is the ECON one, which specifies the details of production and the links between workers and shoppers. In the economy, a homogenous final good is produced in establishments by a stable team of workers and by capital. Each establishment belongs to one of two sectors: High-contact and Low-contact (H- and L-henceforth). These two sectors are a parsimonious way of classifying actual sectors into two groups depending on the strength of the link between production and spreading of the disease. In order to identify these sectors, we use information from the Occupation Information Network (ONET) database to construct measures of physical proximity and frequent interaction between workers and customers in each 2 digit NAICS sector. We then classify the actual sectors that score above the average in both measures as belonging to the H-sector. Examples of these sectors are retail, food, accommodation, and health. Production in the H-sector is likely to cause fast spreading in a pandemic for two reasons. First, H-workers cannot produce from home and thus are more exposed to the disease. Second, as they have numerous and randomly selected daily contacts with customers, they are more likely to spread the disease. The remaining sectors are classified as belonging to the L-sector. In the L-sector, production involves minimal physical proximity and/or interaction with customers. These features imply that production in the L-sector has less impact on infection spreading for two reasons. First, workers in the L-sector have fewer and more stable contacts as they only interact with other workers in their team. Second, a significant fraction of them has the ability to work from home. In addition to the difference in spreading potential, we allow the H and L sector to differ in terms of the marginal product of each worker, so that we can evaluate more accurately the effect on output of shut-down policies

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that target different sectors.

One important feature of the ECON component is that we explicitly model the productive role of customers by assuming that production in the H-sector requires both workers and customers. While workers in the H-sector are only a subset of the population, customers are drawn from the entire population, as every individual in the city shops. This implies that when a pandemic hits and most people severely limit their interactions (either because of shut-down policies, quarantine, or fear) there are two effects on production. The first one is the direct supply effect that reduces production because workers cannot work. The second one is the indirect demand effect, that reduces output because customers do not show up at H-sector establishments where they are an essential factor of production.

We next define a pre-pandemic city equilibrium where heterogeneous workers are allocated efficiently across different establishments and where the shopping capacity of the H-sector satisfies the demand of shopping trips by the population. Using restrictions from the pre-pandemic equilibrium together with sector level data from the New York-Newark-Jersey City (NY-NJ-PA) metro area, we can pick values for the parameters that fully characterize the ECON-component. Before we can use our set-up to conduct policy experiments, we need to pin down two additional set of parameters. The first is the number of contacts between different types of nodes before and during the pandemic. The second is the set of parameters that governs disease progression and transmission (the EPI component). We use the seminal work of Mossong et al. (2008) to pin down the amount of contacts in the pre-pandemic equilibrium, and data from Google Mobility reports to capture the reduction in contacts during the pandemic. Regarding the EPI component, we calibrate its parameters using both evidence from epidemiological studies and by matching key moments of the infection's early phase in the NY-NJ-PA metro area.

Finally, we use the fully calibrated model to perform a number of experiments. The first experiment compares the dynamics of infection in our set-up with the standard SIR set-up. We put the two models on equal footing by choosing parameters in both models to match the dynamics during the early phase (March 8th - April 3rd) of the pandemic in the NY-NJ-PA metro area. We then compare their predictions for the second phase of the pandemic (April 3rd - April 26th) with the data. The main result is that the standard SIR model implies a counterfactually fast spreading of the infection, while the network set-up predicts a plateau of infections, as observed in the data. The reason for this difference is that in the SIR set-up new infections depend on the average fraction of infected nodes in the system so, once total infections reach a critical level (as they did in New York), it progresses rapidly until herd

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immunity is reached. In the network model, however, infections depend on the number of local contacts. Therefore, it is possible that some areas of the network remain untouched by the infection, while at the same time the disease dies out in other areas due to herd immunity at a "local" level.

Our second experiment uses the ECON-component of the model more intensively to study "smart" mitigation policies that can achieve better outcomes during the lock-down phase. These policies can be valuable during a possible second wave of COVID-19, or in future pandemics. We find that policies that reduce the workers shutdown in the L-sector, while at same time increase the workers shutdown in the H-sector can, under some circumstances, achieve a double gain; that is, reduce the spreading of the disease and simultaneously reduce the output loss. It is immediate to see that such policies the spread of the infection. The outcome for output depends on the relative marginal product of labor in the two sectors, which in turn is a function of the amount of capital and of the intensity of the shutdown in each sector. We show that in our NY-NJ-PA metro area case study, for the observed level of shutdown and for the calibrated level of capital in the two sectors, a policy involving a substantial double gain (reduction in infection cases equal to 1.5% of the population and 1% increase in output) could have been implemented.

Our third and final set of experiments concerns the reopening of the business sectors and schools, once the pandemic has passed its peak. We find that the timing and extent of the reopening are crucial. A broad reopening, which includes the H sector or the schools, at a time when the level of infections is still significant in the city inevitably leads to a large second wave. Our set-up suggests two reopening strategies that could avoid a second wave. The first one is to prolong a wide-spread shut down and then reopening only when the level of infections is minimal. The second one is to start the reopening early, but only in the L-sector, which can achieve substantial output gains with little infection growth.

There are three important lessons that we learn from our work. First, the micro structure of the network is essential to understand and predict aggregate infection dynamics. When connections are random and unstable across the network (like in the standard SIR model), an infectious disease spreads fast. When connections are instead clustered and repeated, the same disease stays local and dies out. Layers in our ECON-EPI network lie in between these two extremes, with some layers (the H-sector) being random and unstable and some others (like the family) being more clustered and stable. The dynamics of infection in a city depends on the relative importance of these layers, and policies geared to contain infections are most effective when they can target different layers separately.

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Second, in order to assess the economic cost of policies aimed at containing the infection it is important to specify the micro structure of production. The cost of shutting down a worker is its marginal product. In an undistorted equilibrium, marginal product is captured by the wage; however, during widespread shutdowns like those observed during the COVID-19 pandemic, marginal product can be different (and higher) than the wage, and thus the cost of alternative shutdown policies can be assessed only by specifying the details of production.

Finally, our set-up suggests that there are important complementarities between various types of mitigation policies. For example, we find that reopening schools is only viable if it is preceded by a strict lock-down of many economic activities, which brings infections to a minimal level. Also, we find that when people adopt practices that reduce the transmissibility of the disease (e.g. wearing face-masks), policies that reduce contacts are more effective. A key insight is that the use of a structural model of interaction is necessary to understand and quantify the extent of these complementarities.

The paper is structured as follows. Section 2 summarizes the related literature. Sections 3 and 4 describe the ECON-EPI network and our calibration strategy. Section 5 shows how the network model can help explain the data. Section 6 discusses the policy experiments and Section 7 concludes.

2 Connection to existing literature

The COVID-19 pandemic of 2020 has spurred a new and fast growing literature at the interface between epidemiology and economics, studying the effects, both on infection and economic outcomes, of different policies geared to containing the spreading of the disease.

A first generation of papers has modeled the epidemiological component using versions of the standard SIR random mixing model, as in Kermack and McKendrick (1927). Examples of these works include Acemoglu et al. (2020), Alvarez et al. (2020), Atkeson (2020), Eichenbaum et al. (2020), Favero et al. (2020), Glover et al. (2020) and Jones et al. (2020).

Modern research in epidemiology has moved beyond this classical framework to explicitly model the patterns of interaction among agents and makes extensive use of network theory to predict the pattern of infections in a city or in a country.[1] One of the main contributions of our paper is to integrate the network modeling of infection from epidemiology in an economic model of a city, where the network plays an explicit role both in the transmission

[1]See Keeling and Eames (2005) and Jackson (2010) for excellent surveys of the literature on networks in epidemiology.

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of infection and in the creation of economic value. We now briefly discuss how our paper is different from other recent and excellent works that also use network theory to study the COVID-19 pandemic. Karaivanov (2020) analyzes the diffusion of COVID-19 in an abstract network and makes the point that transmission is different from the one in the standard SIR model. However he restricts his attention to the epidemiological component. Baqaee et al. (2020) and Akbarpour et al. (2020) both use a network framework to analyze the economic and epidemiological effects of containment and re-opening policies. Baqaee et al. (2020) focus on aggregate (US) outcomes, while Akbarpour et al. (2020) focus, as we do, on metro-level outcomes. There are two important differences that distinguish our work from theirs. The first is that we model the network differently. In their works the main heterogeneity across nodes rests on the number of contacts. Nodes in our network, in addition to being heterogenous in terms of number of contacts, are also heterogenous in terms of the pool from which they draw their daily contacts.[2] This feature of the contacts, which we refer to as "stability", not only is empirically relevant, as it captures the different degree of randomness of daily contacts in different occupations, but is also quantitatively important to explain infection dynamics. The second difference is in the modeling of the production structure. Both papers assume labor is the only factor of production, while we use an establishment production function that, in addition to labor, uses capital and (for retail establishments) customers as inputs. This production function allows to evaluate the output costs of workers' shutdown more accurately, as well as the impact on output of the reduction in shopping contacts (i.e. demand effects).

Our work is also related to a number of more empirical studies exploring the role of heterogeneity across sectors and across workers in the spreading of the infection and in designing efficient containment policies, such as Benzell et al. (2020), Dingel and Neiman (2020), Kaplan et al. (2020), Leibovici et al. (2020), and Mongey et al. (2020).

3 The ECON-EPI network

We now describe the details of the ECON-EPI network, a model designed to capture human and economic interaction in a typical US metropolitan area. We first present the network structure, i.e. the links that connect individuals in their different activities. We then proceed to specify the EPI component, i.e. how infections progress and spread through the network.

[2]This heterogeneity has been explored in Acemoglu et al. (2013), Acemoglu et al. (2010) and Azzimonti and Fernandes (2018) in information networks.

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Finally, we describe the ECON component, i.e. how interactions in the network produce output. In this part, we first specify a pre-pandemic steady state equilibrium, which describes the normal state of economic affairs before the pandemic. We then discuss how the arrival of a disease and the adoption of containment measures affect economic activity during the pandemic period.

3.1 A multilayered network

We construct a multilayered network where individuals of different characteristics (age, employment status, public transportation usage, etc.) interact with each other. The set-up is necessarily stylized. Nevertheless, it has enough richness to capture key aspects of the social distancing policies that have been implemented during the 2020 COVID-19 pandemic. Time is discrete and the network is generically represented by a $M \times M$, time varying, adjacency matrix $\mathbf{G_t}$, where each node represents an individual. Individuals are heterogeneous in several dimensions. In terms of age, there are adults and kids. Kids are a fraction ν_K of total population and go to schools. In terms of employment characteristics, adults may work in different sectors or be out of the workforce. Additionally, individuals differ in the size of their household, their number of neighbors, and their use of public transportation. We now proceed to describe the various layers connecting individuals. These layers affect the probability for each individual of contracting and spreading the disease throughout the network.

Households and Neighbors: Households can be single member (composed of one adult) or two-member, composed of an adult and a kid. Members of the same household are fully connected through intra-household links. These links form the first layer of our network, contained in the adjacency matrix $\mathbf{G}^H$. The left panel of Figure 1 shows an example of household links in a city with 12 households, where the circles represent adult members and the stars represent kids. Households are placed next to each other on a ring (as in Watts and Strogatz 1998), and each household member is connected all the members of N neighboring households on the left and on the right. The neighborhood links form the second layer of our network and are recorded in the adjacency matrix $\mathbf{G}^N$. Household and neighborhood links are 'short-stable links,' meaning that they are active at every point in time, and connect individuals who are close to each other.

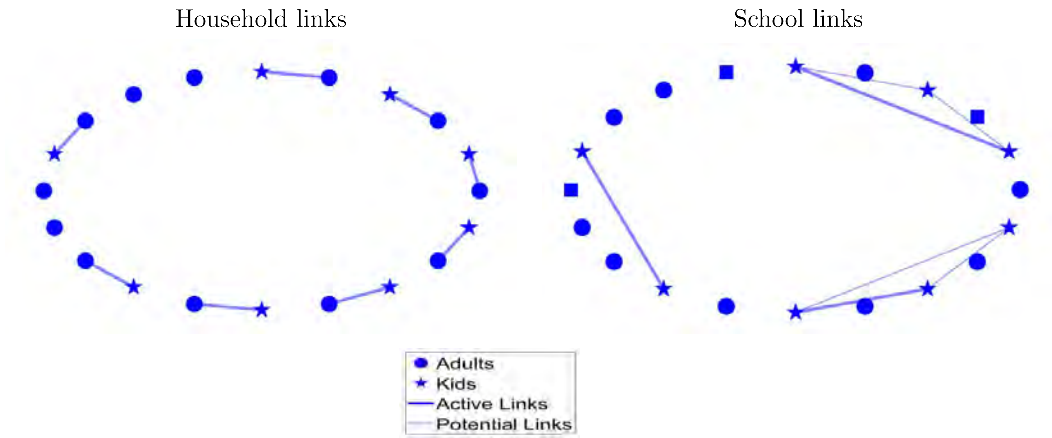

Figure 1: Households and Schools

Schools: Our third layer involves a school system where each day every kid interacts with a subset of other kids in her school. Each school draws kids which live close to each other, and the school size Q determines the pool of potential interactions of each kid. We refer to these links as "potential" school links and their associated adjacency matrix is denoted by $\mathbf{G}^S$. The right panel of Figure 1 shows the potential and active links for three schools (two of size 3 and one of size 2) for the same example network in the left panel of the figure. Note that we refer to school links as "potential" because, in contrast to the links in the first two layers, they are not always active: each kid has active links only with a subset of her schoolmates, which is randomly drawn every period. We define school links as 'short-unstable' meaning that they connect individuals who are geographically close to each other, and that they change their status (from active to inactive) over time. The reason for introducing this layer is to later evaluate the effect of school closures and reopenings on the spreading of the infection.

Public Transportation The next layer of the network specifies interactions through public transportation. A fraction ϕ of individuals uses public transportation. Each public transportation vehicle has a capacity of seating P individuals, and we assume that agents living close to each other use the same public transportation vehicle. This implies that each individual using public transportation is potentially connected to locally close individuals who also use public transportation. Potential public transportation links are summarized

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in the adjacency matrix $\mathbf{G}^P$. During each public transportation trip, each individual interacts with a random subset of the vehicle occupants. Therefore, individuals who use public transportation will be more exposed to the disease than those who use private means of transportation.[3]. Like school links, public transportation links are short and unstable. The difference between the two is that school links involve only kids, while public transportation connects adults as well as kids.

Workplace A fraction of adults in the network work. The workplace layer describes how working adults interact with each other and with the rest of society. The city features two distinct workplaces, which we label L (for Low-contact) and H (for High-contact). In the L-workplace (which is meant to capture sectors like manufacturing) there are stable teams of L-workers. In the H workplace (which is meant to capture sectors like retail or hospitality) there are similar teams of workers, but these workers are also connected with a time-varying subset of customers. We now describe in more detail the two workplaces.

L-Workplace L-Workers are a share ν_L of adults. Some of them (e.g. software developers) have the opportunity of working from home, which they will use in different intensity before and after the pandemic. The remaining members (e.g. assembly line workers) cannot work from home, and they are all connected to each other when working. The lightly colored nodes in the left panel of Figure 2 are a team of L-workers. Note that three of them are connected to each other, while one (labeled home worker) is not connected. For production purposes the home worker is part of the team, but it can perform work without contact (and hence without risk of contagion) with the other team members.

H-Workplace H-Workers are a share ν_H of adults and they represent occupations that, for the purpose of production, involve stable contacts with co-workers (just like the L-workers) as well as unstable contacts with external customers (such as retail). The right panel of Figure 2 illustrates a team of H-workers. The lightly colored nodes represent the members of the team. Note that each worker in the team has potential links with other nodes in the network (potential customers, connected to the workers by the thin lines), and in each period some of these links become active (actual customers, connected to the workers by the thick lines). Note that customers are not connected to each other. This captures the fact that individuals from certain professions (doctors, bartenders, shop clerks) may come

[3]See Harris 2020 for a study on the role of public transportation in spreading the COVID-19 pandemic in New York City

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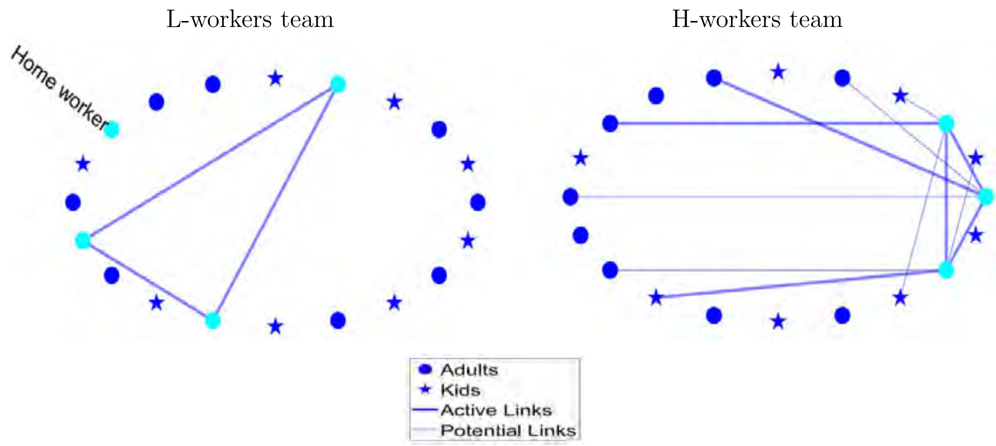

Figure 2: Workplaces

into contact with several clients during a day, sequentially, so their visits do not overlap. Finally observe that due to the nature of their work, H-workers do not have the opportunity of working from home.

Worker links are, thus, intrinsically different from school links or public transportation links for two reasons. First, they include long links, connecting individuals in the network who are not necessarily in the same geographic area. Second, the number of connections of each individual worker can be different, with L-workers having only stable links, and H-workers having stable and unstable links. For convenience, we record worker links in two adjacency matrices: $\mathbf{G}^W$, which records all co-worker links (stable) in the H and L sector, and $\mathbf{G}^C$ which records worker to customer links in the H-sector (unstable).

Network Clocks An important network feature, for the purpose of disease spreading, is the presence of unstable links between nodes. Connections in the household layer, the neighborhood layer, and among teams of workers—in the workplace layer—are stable, as individuals are linked with the same set of people every period (e.g. their network links are always active). On the other hand, interactions in the school layer, the public transportation layer, and between shoppers and workers—in the workplace layer—are inherently unstable (e.g. only a subset of potential links are active every period). To model this, we incorporate a *clock* in the spirit of Acemoglu et al. (2010) and Acemoglu et al. (2013). More specifically, for all $t \geq 1$, we associate a *clock* to every link of the form (i,j) in the original adjacency matrix $\mathbf{G}^i$ (where $i = S, P, C$) to determine whether the link is activated or not at time t. The ticking of all clocks at any time is dictated by i.i.d. samples from a Bernoulli Distribution with fixed parameter $\varrho_i \in (0, 1]$, meaning that if the (i,j)-clock ticks at time t (realization 1 in the Bernoulli draw), the connection between agents i and j is active at time t. This is meant to capture two kids in the same school having lunch together on a given day, two persons sitting next to each other in the subway, or a customer and a cashier interacting over a transaction. The Bernoulli draws are represented by the $M \times M$ matrix of zeros and ones c_t^i. Thus, the adjacency matrices for school, public transportation and worker-customers networks evolve stochastically across time according to

$$\begin{aligned} \mathbf{G}_t^i &= \mathbf{G}^i \circ c_t^i \qquad (1) \\ \text{where } i &= S, P, C \end{aligned}$$

City Network: Finally, we superimpose the layers described so far to construct a meta network which corresponds to our synthetic city. The adjacency matrix capturing all links within a city, $\mathbf{G_t}$, is constructed as a weighted sum of the different layers. The weights correspond to the relative importance of each layer, capturing that individuals spend different amounts of time interacting with others in different social spheres. In particular, we have that

$$\mathbf{G_t} = \omega^H \mathbf{G}^H + \omega^N \mathbf{G}^N + \omega^W \mathbf{G}^W + \omega^S \mathbf{G}_t^S + \omega^P \mathbf{G}_t^P + \omega^C \mathbf{G}_t^C. \qquad (2)$$

Each element in $\mathbf{G_t}$, denoted by $g_{i,j,t}$, summarizes the link between two individuals i and j at time t, weighted by the strength of their relationship.

3.2 The EPI component

The spread of the disease within our multilayered network is the result of two types of events: the person-to-person transmission of the disease (which depends on the network) and the progression of the disease for a given infected person, which is independent from the network structure. Our modeling of the disease progression closely follows a SEIR structure, a variant of the SIR model that is common in the epidemiological literature, where we added the possibility of an "asymptomatic" branch. This assumption is motivated by the fact that, during the COVID-19 pandemic, many infection cases went undetected, either because symptoms were mild, or because testing was not available. These cases were never officially

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recorded as infected, and transited directly to the recovered stage. However, according to several studies, they significantly contributed to the spread of the disease.[4]

Each individual node can be, at each point in time, in one of six health states: **S**usceptible, **E**xposed, **I**nfected-**A**symptomatic, **I**nfected-**P**re-symptomatic, **I**nfected-**S**ymptomatic, and **R**ecovered.

(1) Susceptible (S): a node which has not been exposed to the disease, but may contract it in the future.

(2) Exposed (E): a node which has been in contact with an infected node and has contracted the disease. Exposed nodes are not infectious and continue to perform normal activities. However they will transit with certainty to one of the infectious states the day following the exposure.

(3) Infected Pre-symptomatic (IP): a node which is infected and will show symptoms in the future. Nodes at this stage do not know they are infected, so they continue to perform normal activities. They transmit the disease with probability π.

(4) Infected Symptomatic (IS): a node which is infected and shows symptoms. IS nodes are removed from all layers of the network, with the exception of the household layer. They transmit the disease with probability π.

(5) Infected Asymptomatic (IA): a node which is infected, but does not and will not show severe symptoms. These nodes do not know they are infected, so they continue to perform normal activities. IA nodes, when in contact with an S node, transmit the disease with probability $\eta\pi$, with $0 \leq \eta \leq 1$.

(6) Recovered (R): a node which is no longer infected. Recovered nodes are immune to the disease and can resume normal activities.

Note that all nodes in an infected state can transmit the disease to susceptible nodes, although the infected asymptomatic are less likely to transmit. The transition between states is illustrated in Figure 3. A susceptible node i contracts the disease at time t with probability $p_{i,t}$ and if it does so, moves to the exposed state. An exposed node transitions to the asymptomatic stage with probability α and to the pre-symptomatic stage with probability $1-\alpha$. A pre-symptomatic node moves to the symptomatic stage in each period with

[4] See, for example, Li et al. 2020.

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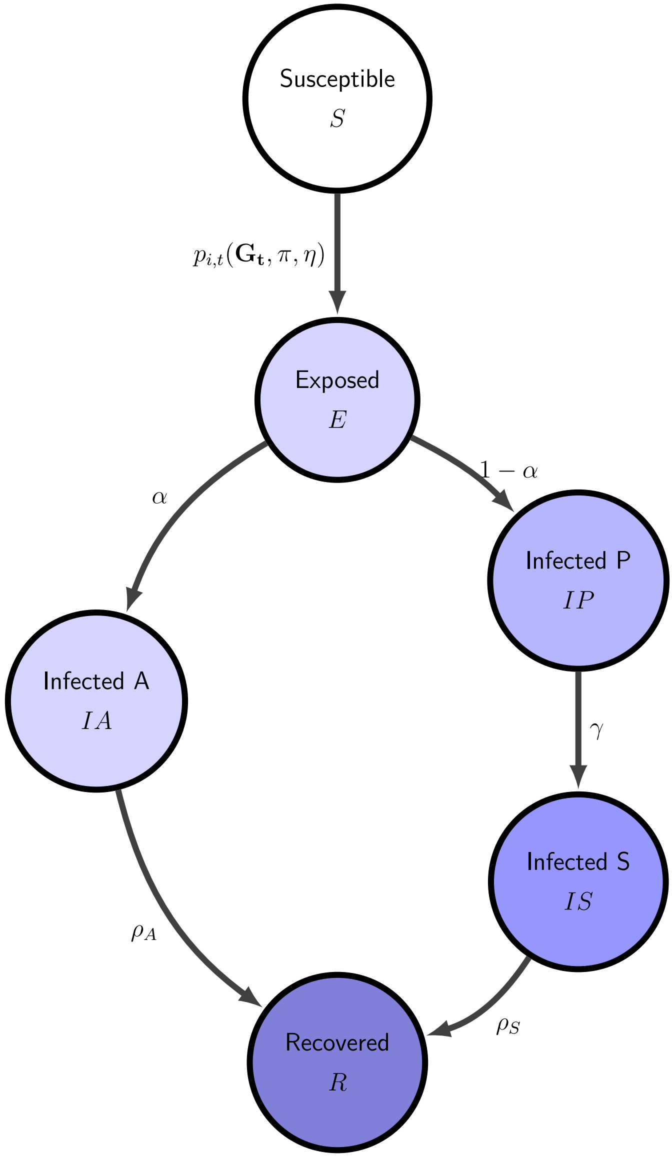

Figure 3: Transition between health states

probability γ and a symptomatic node moves to the recovered stage with probability ρ_S. An asymptomatic node, on the other hand, has a probability ρ_A in each period of moving directly to the recovered stage. Finally, recovery is an absorbing state. The key object of our analysis is $p_{i,t}$, the probability that a susceptible node i contracts the disease in period t. The probability $p_{i,t}$ is a function of the active contacts of node i at time t (encoded in $\mathbf{G_t}$), of their health status and on the odds of contracting the disease conditional on meeting an infected node (governed by the parameters π and η). In particular we can write

$$p_{i,t}(\mathbf{G_t}, \pi, \eta) = 1 - \prod_{j=1}^{M}(1 - \pi\eta^{A(j,t)})^{g_{i,j,t}I(j,t)}. \tag{3}$$

where $g_{i,j,t}$ is the ith, jth element of $\mathbf{G_t}$, $I(j,t)$ is an indicator function that equals 1 when node j is infected (either pre-symptomatic, a-symptomatic or symptomatic) at time t, and zero otherwise, and $A(j,t)$ is a similar indicator function for the infected-asymptomatic status. This equation makes it clear that the spreading of the disease in the economy depends not only on the disease prevalence (captured by $I(j,t)$ and $A(j,t)$) and on the biological transmissibility (captured by π and η), but also on the network structure summarized by $\mathbf{G_t}$.

3.3 The ECON Component

Individual nodes, together with the network structure, produce, at each point in time, new infections and economic output. This section describes how output gets produced over the network and how it is affected by social distance policies and by behavioral changes that result from the progression of the infection. The two workplaces described in Section 3.1 map into two sectors where output is produced. Both sectors produce the same homogenous good (which is also the numeraire) and production is organized in establishments. In the L-sector there are Q_L ex-ante identical establishments, each endowed with the same amount of fixed capital K_L. These establishments employ teams of L-workers. In the H-sector there are also establishments which hire teams of H-workers, and we allow capital to be potentially different across establishments. As we think of these two sectors as having a substantially different occupational mix, we assume that workers cannot move across sectors.[5] In the L-sector, production requires L-workers and capital, while in the H-sector, production requires H-workers, capital, and customers. We first describe a pre-pandemic steady state equilibrium,

[5]The details about mapping actual sectors of the economy into these two stylized sectors are discussed in Section 4.

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where there are no infected nodes and the level of economic activity is stable over time, and then move on to describe how economic activity evolves as the disease hits the city and containment measures are adopted.

3.3.1 Pre-pandemic equilibrium

L-Sector Recall that establishments in this sector are homogenous. Each establishment produces y_L units of output according to

$$y_L = K_L^{\theta} n_L^{1-\theta}$$

where n_L denotes units of labor. Notice that n_L is labor input which is not necessarily the same as employment, as not all L-workers supply the same amount of labor input. In particular, consistently with recent empirical work by Dingel and Neiman (2020) and Leibovici et al. (2020), we assume that a fraction ω of L-workers can work from home, and the labor input (or productivity) of these workers is δ_ω% higher than the labor input of those that cannot work from home. Given the wage rate per unit of L-work w_L, the establishment manager chooses labor input to maximize profits, which are given by $y_L - n_L w_L$. This implies that per establishment labor demand is given by

$$n_L = K_L \left(\frac{1-\theta}{w_L} \right)^{\frac{1}{\theta}}. \tag{4}$$

Labor supply of the L-workers is inelastic and is simply given by the total numbers of L-workers times their average labor input. A pre-pandemic equilibrium is then a wage rate w_L and quantity of L-labor per plant n_L such that, i) given wages, n_L is chosen optimally by the plant manager and ii) labor market for L-workers clear. Equation 5 summarizes these two conditions

$$\underbrace{Q_L n_L = Q_L K_L \left(\frac{1-\theta}{w_L} \right)^{\frac{1}{\theta}}}_{\text{Labor Demand}} = \underbrace{\Big[\omega(1+\delta_\omega) + (1-\omega) \Big] \nu_L (1-\nu_K) M}_{\text{Labor Supply}}, \tag{5}$$

where ν_L denotes the share of adults which work in the L-sector and $(1-\nu_K)$ the share of adults in the population, implying that $\nu_L(1-\nu_K)M$ is the total number of individuals who work in the sector, while $\omega(1+\delta_\omega) + (1-\omega)$ is their average effective labor.

H-Sector The locking down of retail establishments has been at the centerpiece of the policy discussion during the 2020 COVID-19 pandemic. Although it has been widely acknowledged that larger retail establishments lead to fast spreading of the disease, there has

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been much less emphasis on the fact that large retail establishments are, on average, more productive (see, for example, Foster et al. 2006), and thus shutting down workers in those establishment might be more costly. In order to capture this trade-off we introduce heterogeneity in H-establishments. We consider two types of establishments: small and large, indexed by $j = 1, 2$. There are Q_{H1} small establishments (mom and pop corner stores) which have less capital, and have customer and employee bases drawn from individuals in a geographically close area. There are Q_{H2} large establishments (e.g. large shopping malls, concert venues, and stadiums) which have more capital and have customer and employee bases drawn from the entire network. Each establishment of type j in the H-sector produces y_{Hj} units of output according to

$$y_{Hj} = K_{Hj}^{\theta}\left(\min\left\{\frac{K_{Hj}d}{\mu}, n_{Hj}\right\}\right)^{1-\theta},$$

where K_{Hj} denotes the capital of establishment of type j ($K_{H1} < K_{H2}$), n_{Hj} denotes the number of workers (which in this sector are homogenous) employed by establishment of type j, μ is the number of customers that a H-worker can attend to and d represents the number of customers (per unit of capital) which shows up at establishment i. This assumption captures that in the H-sector customers and workers are complement in production: if a customer does not go to the establishment, a sale does not materialize and output is not produced. In addition, if there are too few workers, they may not be able to serve all the customers that come to the establishment. The establishment manager takes as given the wage rate w_H and the demand d and hires workers to maximize profits, which are given by $y_{Hj} - n_{Hj}w_H$. This implies that labor demand in establishment of type j is given by

$$n_{Hj} = K_{Hj}\min\left\{\left(\frac{1-\theta}{w_H}\right)^{\frac{1}{\theta}}, \frac{d}{\mu}\right\}. \tag{6}$$

Similarly to the L-sector, the labor supply of the H-workers is inelastic and is given by the total numbers of H-workers, which is equal to $M(1-\nu_K)\nu_H$. The last element that is needed to define a pre-pandemic equilibrium is the determination of d. Recall that in our model city there are M individuals, and each person makes s shopping trip every period. It follows that the total number of customers of the H-sector is Ms. The customer capacity of the H-sector is instead given by the sum of all workers employed in that sector, times the number of customers a worker can attend, μ. Since in equilibrium the sum of all workers employed in the H-sector is the labor supply in the sector, equilibrium customer capacity is given by $\mu M(1-\nu_K)\nu_H$. We then assume that in a pre-pandemic equilibrium, the number of shopping trips per person is such that total shopping trips equals customer capacity of the H-sector, that is $s = \mu(1 - \nu_K)\nu_H$.

To sum-up, a pre-pandemic equilibrium in sector H is a wage rate w_H, a quantity of H-labor per type of establishment n_{Hj} and an amount of customers per capital d, such that, i) given wages and customers, n_{Hj} is chosen optimally by the establishment manager, ii) labor market for H-workers clear and iii) the total number of shopping trips equals the customer capacity of the H sector.[6] Note that our concept of equilibrium guarantees that in every pre-pandemic period every shopper in each of her/his shopping trip is assigned to an H-worker that can serve her. Note that the maximization of profit at the establishment level, plus the heterogeneity in capital imply that type 2 establishments will employ more labor, make more sales and have higher output.

3.3.2 Production during the pandemic

In the pre-pandemic equilibrium output is equal across establishments of the same type and is constant over time. During the pandemic, however, output can change over time, and it can be different across establishments of the same type. As discussed in Section 3.2 nodes that are infected and show symptoms are prevented from working and shopping. Moreover, as the disease spreads, policies are introduced that may prevent also a fraction of healthy workers from working at their establishment. We denote by n_{Lit} the number of L-workers that show up at work in establishment i in period t, by n_{Hjit} the number for H-workers that show up at work in H-establishment i of type j (large or small) in period t, and finally by d_{it} the number of customers (per unit of capital) that will show up to shop at H-establishment i in period t. By assumption, in the short run establishments can not replace workers, therefore when the number of workers falls, establishment output will also fall. Moreover, when a customer assigned to an H-establishment is sick and does not show up to shop, the output of that establishment also is reduced. We can now define Y_t, i.e. the total production of the city in period t as

$$Y_t = \underbrace{\sum_{i=1}^{Q_{H1}} \left[K_{H1}^{\theta} \left(\min\left\{ \frac{d_{it} K_{H1}}{\mu}, n_{H1it} \right\} \right)^{1-\theta} \right]}_{\text{Output of small H establishments}} + \underbrace{\sum_{i=Q_{H1}+1}^{Q_{H1}+Q_{H2}} \left[K_{H2}^{\theta} \left(\min\left\{ \frac{d_{it} K_{H2}}{\mu}, n_{H2it} \right\} \right)^{1-\theta} \right]}_{\text{Output of large H establishments}}$$

[6]For simplicity, we do not develop an explicit theory of the individual choice of shopping trips. A possible way of doing so, that would be consistent with our equilibrium restriction, would be to have the individual benefit of shopping trips to be decreasing in the tightness of the shopping market, i.e. in the ratio between shoppers and customer capacity

$$+ \underbrace{\sum_{i=1}^{Q_L} K_L^{\theta} n_{Lit}^{1-\theta}}_{\text{Output of L establishments}}$$

The time series for Y_t during the pandemic is a key object of interest in our policy experiments below, as it summarizes the economic impact of the pandemic and of the various measures of pandemic control.

4 Calibration

In this section we describe how we set the values for the parameters of the ECON-EPI network, in order to numerically assess the impact of the pandemic and the effects of several policies.

4.1 Demographics and Public Transportation

We calibrate our model to a 5% synthetic version of the New York-Newark-Jersey City (NY-NJ-PA) metro area, which in 2019 had a population of approximately 20 million. The percentage of kids in the population ν_K is set to 28% so that the synthetic city has 40% of households with kids, which matches the percentage of households with kids in the metro area from the 2014-2018 American Community Survey (ACS). The percentage of non working adults ν_N is set to 37%, to match the employment to population ratio for persons over 18 in the metro in 2019.[7] The share of agents using public transportation, ϕ, is set to 32% in order to match the percentage of individuals who report commuting to work using public transportation in the NY-NJ-PA metro area from the 2014-2018 ACS.

4.2 Workplace

An important aspect of the calibration is to map workers in the data to workers in the two sectors of the model: the H and L sectors. In order to do so, we first work with occupations. Recall that there are two key features that characterize the H-sector: one is the physical proximity with other people (so that infection can be transmitted) and the second is the instability of the contact with customers (which also speeds up the spread of the disease). To capture these two features in an occupation, we use two questions in the ONET database.

[7] Employment figures are from the BLS and population figures are from the Census.

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Table 1: Demographics and Public Transportation

Parameter Name	Symbol	Value	Source
Demographics			
Total Population	M	1,000,000	Census Data: ACS 2018
Share of Kids	ν_K	28%	American Community Survey
Share of Non-working Adults	ν_N	37%	American Community Survey
Public Transportation			
Share using Public Transportation	ϕ	32%	American Community Survey

The first one asks about physical proximity to other people on the job, while the second one asks about the importance of interactions with external customers.[8]

The answers to these questions can be used to construct two indexes, both ranging from 0 to 100, that give, for each 6-digit occupation, measures of physical proximity and external interactions. Next, using a standard crosswalk, we compute similar indices for all the private sectors at the 2-Digits NAICS level, where the index for sector i is the average of the indices of each occupation j in that sector, weighted by the national employment share of occupation j in sector i. This procedure yields indices of physical proximity and external interactions for all the 2-digits NAICS sector. Figure 4 shows these (standardized) indices for all the NAICS 2 digits private sectors.

The shaded northwest quadrant highlights the 5 sectors which have both indices above the mean; we thus construct the H-sector by aggregating them, and the L-sector by aggregating all the others.

In Table 2, we report key characteristics of workers in the two sectors using employment figures from the Census Statistics of US Business (SUSB) for the NY-NJ-PA metro area in 2016. The L-sector employs more workers (54% v/s 46%), and workers in that sector

[8]Specifically the first question (ONET question 21) is "How physically close to other people are you when you perform your current job?" and the second question (ONET question 8) is "In your current job, how important are interactions that require you to deal with external customers (as in retail sales) or the public in general (as in police work)?"

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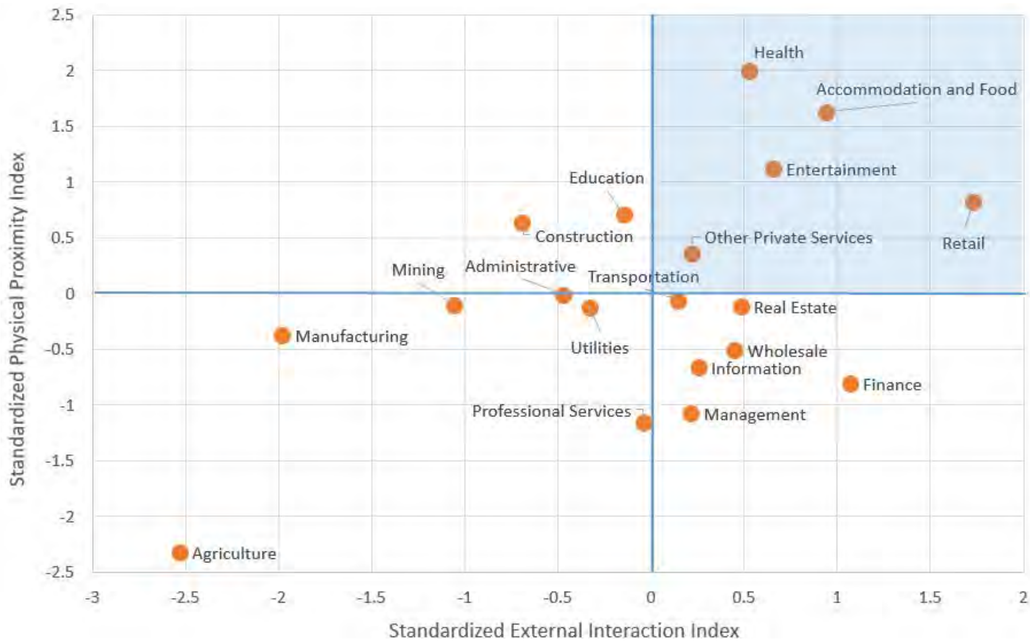

Figure 4: Identifying high contact sectors

Table 2: Characteristics of workers in H and L Sectors

	Share	Avg. yearly wages ($)	Share Home workers	Home wage premium
L-sector	54%	$94k$	7%	16%
H-sector	46%	$40k$	3%	6%

have higher average yearly wages ($94k$ v/s $40k$). In the last two columns we compute the fraction of workers in each sector that work from home and a measure of their wage premium (relative to those who do not work from home). Note that in the L sector there are many more workers that work from home and that the annual wage of the home L-workers is roughly 16% higher than the wage of the non home workers in the same sector.[9]

In the next section, we use these numbers to pin down the labor supply and the techno-

[9] To measure the share of workers that work from home we first use ACS data to compute the share of home workers in each 2-digits NAICS sector and then take a weighted average of these percentages, where the weights are the employment shares of each NAICS sector in our 2 macro sectors. Similarly to compute wages of home workers we take a weighted average of the wages in each sector, where the weights are the shares of home workers in each NAICS sector.

logical differences across the two sectors.

4.3 Labor and Technology

The general logic of this section is that restrictions from the pre-pandemic equilibrium (see Section 3.3.1), plus data from firms and workers as described above, pin down the parameters that characterize the labor supply and the technology in the L and H sectors. All the parameters are reported in Table 3 below.

We first use statistics on home workers and on their wages reported in Table 2 to pin down the parameters ω and δ_ω, which determine: (i) the fraction of L-workers that can work from home and (ii) the ratio of their wage relative to the wage of those who cannot work from home in the L-sector.[10] In order to determine the fraction of L-workers who can work from home in our series of experiments, we use two types of information. In Table 2, we report that in the L-sector 7% of workers already work from home before the pandemic hits. However, this is a lower bound for the fraction of workers that can actually start tele-commuting once the level of infections starts to increase and social-distance and lockdown measures are implemented. Dingel and Neiman (2020) estimate the fraction of workers that can potentially work from home in each occupation based on occupational characteristics. We compute their measure for each sector and, aggregating by sector, we find that the fraction of L-workers that can in principle tele-commute is 49.7%. We view this number as an upper bound as, in the short run, it is unlikely that such a large percentage of workers can switch to tele-commuting. For this reason, we set the fraction of workers who can actually work from home once the pandemic hits, ω, to 28% (which is the mid-point between the lower and upper bound).

In summary, we consider a pre-pandemic equilibrium with $\omega = 7\%$ and increase the number of L-workers working from home to $\omega = 28\%$ during the pandemic. We assume that non-home workers supply 1 unit of labor input and home workers supply $1 + \delta_\omega = 1.16$ units, in order to match the wage differences between the two groups in the L-sector. We then use demographic statistics from Table 1, plus worker statistics from Table 2, to pin down the parameters ν_L and ν_H, which denote the share of adults working in the L and H sectors, respectively. All these parameters determine the total labor supply (in units of labor input) in both sectors.

Both sectors share constant returns to scale production functions, where capital share is common and given by θ. We estimate θ using the standard methodology outlined in Cooley

[10]Recall that, since few workers in the H-sector work from home, we assume that the percentage of H-workers that work from home is 0, both before and during the pandemic.

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and Prescott (1995), using 2018 data for the New York Metro Area.[11]

Table 3: Labor and Technology Parameters

Parameter Name	Symbol	Value
Share of Capital Income	θ	33%
L-Sector		
Share of adults working in L	ν_L	34%
Share of L-workers that can work from home	ω	28%
Home premium	δ_ω	16%
Number of establishments (14 wkrs)	Q_L	18,400
Capital per unit of labor	$\frac{K_L}{n_L}$	3.4
H-sector		
Share of adults working in H	ν_H	29%
Number of small establishments (4 wkrs)	Q_{H1}	12,000
Number of large establishments (50 wkrs)	Q_{H2}	3,500
Number of customers per H-worker	μ	10
Capital per unit of labor	$\frac{K_H}{n_H}$	0.26

Given θ we can normalize the wage of a unit of labor (which is equivalent to the wage of a non-home worker) in the L-sector to 1 and use the establishment labor demand (Equation 4) to pin down the labor demand per unit of capital. We then use the labor market clearing (Equation 5) to pin down the total capital in the sector $Q_L K_L$. Note that in the pre-pandemic equilibrium the number of establishments Q_L is not determined separately from the capital

[11]The estimate is the ratio between capital income (consumption of fixed capital plus rent, interest and dividend income) and the sum of capital income plus labor income (compensation of employees). Data for rent, interest and dividend income, and for compensation of employees is available from BEA regional tables. Consumption of fixed capital is computed by first taking the ratio of consumption of fixed capital to GDP on national data for 2018 (the ratio is 16%) and then multiplying it by the metro area GDP.

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per establishment K_L, so we simply pick Q_L so that the number of workers per establishment in the model is 14, which matches the number of workers per establishment in the NAICS sectors that compose our L-sector.[12]

Now moving to the H-sector, we use, as we did in the L-sector, the establishment labor demand (Equation 6) to pin down the labor demand per unit of capital. We then use the labor market clearing to pin down the total capital in the sector $Q_{H1}K_{H1} + Q_{H2}K_{H2}$. We pick Q_{H1} and Q_{H2} to match features of the establishment size distribution in the NY-NJ-PA metro in the NAICS sectors that comprise our H-sector. In particular, we choose the size of the small establishments to match the average establishment size of the firms in the H-sector that have less than 20 employees. This gives a number of 4 employees for the small establishment and 50 employees for the large establishments. This choice, together with equilibrium restrictions, implies that in the model 22% of H-workers are in 4-employee establishments (so that we match the employment share of small establishments). We denote this share as ν_{H1}. The values of Q_{H1} and Q_{H2} are reported in Table 3.

The remaining parameter to be determined in the H sector is μ, that is the number of customers that a worker can attend to in a day. Recall that, in a pre-pandemic equilibrium, in the H-sector the number of customers is equal to the total customer capacity. In the next section, we calibrate the equilibrium shopping trips (s) to be 2 per person, so that the total number of customers in a day is $2M$. This implies, given the share of H-workers in the population, that the parameter μ is approximately 10; that is, an H-sector worker serves an average of 10 customers per day. One final important statistic reported in Table 3 is the capital per unit of labor, which is higher in the L-sector (3.4) than in the H-sector (0.26). The magnitude of this gap is identified from data on the wage differential (see Table 2) between workers in the two sectors. The reason why a unit of labor used in the production of the final good in the L-sector receives a higher compensation than a unit of labor used in the production of the final good in the H-sector, is that labor in the L-sector works with more capital.[13]

[12] In the model, the number of workers per establishment is smaller than the quantity of effective labor as the average worker, due to higher productivity of home workers, supplies more than one unit of effective labor.

[13] In our set-up, we have abstracted from differences in human capital among the workers in the two sectors, and attributed all the differences in wages to differences in physical capital. Since in the short run physical capital is fixed, the results concerning output losses from shutting down workers in the two sectors are independent on whether we attribute wage differences to physical or human capital.

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4.4 Network Contacts and Weights

The number of contacts each person has on each layer, and the weights of different layers play an important role in the spreading of the disease through the network. Our main reference for setting these in the model is the work by Mossong et al. (2008), which, using a common paper-diary methodology, has collected data on various characteristics of daily face-to-face interactions for a sample of over 7000 persons in 8 European countries.

The number of contacts of various individuals in different layers in the model and the targets from Mossong et al. (2008) are reported in the first two columns of Table 4.

Mossong et al. (2008) reports that on average each individual has 5.2 contacts in the household and during leisure activities. We map these contacts with model's contacts that take place within the household and neighborhood layers. Since the average household size in the model is 1.6, we impose that each household has on average 3 neighbors (some households have two neighbors and some have four), so that each individual has an average of $1.6+3\cdot1.6-1 = 5.2$ household/neighbor contacts. Mossong et al. (2008) also reports that, on average, each individual experiences 2 contacts during shopping and 0.4 while traveling. We set the number of shopping trips per person and the number of meetings while using public transportation in the model to match these two figures.

Moving now to the differences between kids and adults, Mossong et al. (2008) reports that kids between the ages of 0 and 19 have on average 15.3 contacts, and adults have on average 12.4 contacts. In the model, we set the number of school contacts (which are specific to kids) to match total kids contacts. For adults, the number of contacts is more heterogenous. A fraction of adults (the non-workers) have no contacts resulting from work. Another fraction (the L-workers) have contacts resulting from meeting their team (of size T_L) of co-workers, where the team of workers is meant to capture the set of co-workers with which a worker interacts more closely. Finally, the H-workers have contacts resulting from the team of co-workers (of sizes T_{H1} and T_{H2}) and from meeting with customers (μ). Since we do not have much hard evidence on the size of workers teams, we simply set the size of the team of H-workers in the small establishments T_{H1} to 2 (mom and pop stores) and set $T_{H2} = T_L = 5$ so to match the total number of adult contacts.[14] Notice also that this choice for the size of teams together with the data on establishment sizes in Table 3 implies that an L-establishment employs 3 teams, a H-large establishment employs 10 teams and a H-small establishment employs 2 teams.

[14] A team size of 5 will result in 4 co-worker contacts for the H-worker, and only 3.7 contacts for the L-worker because a fraction of the workers work from home.

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Table 4: Network Contacts and Weights

Person type	Layer	Actual Contacts		Weight	Contact Pool
		Model	Mossong		
All:	Home and Neighbor	5.2	5.2	[22%, 10%]	-
	Shopping overall	2	2	10%	
	small	$2v_{H1}$			4
	large	$2(1-v_{H1})$			$\tilde{v}v_H M$
	Public Transport	0.3	0.4	4%	54
Kids:	Total	15.5	15.3		
	School	8		22%	26
Adults:	Total	12.3	12.4		
	Work				
	H-small (co-workers)	1		22%	-
	H-small (customers)	10		22%	56
	H-large (co-workers)	4		22%	-
	H large (customers)	10		22%	M
	L (co-workers)	3.7		22%	-

Mossong et al. (2008) also reports information on the average duration of contacts, by contact type (daily, weekly and first time). We identify contacts in the household, work and school layers as daily, with an associated average duration of 3 hours. We identify shopping and neighborhood with weekly contacts, with an associated average duration of 1.4 hours and finally we think of contacts during travel as first time contacts, with an average duration of 0.5 hours. These figures results in weights of each layer (normalized to sum to 1) which are reported in the third column of Table 4. These weights are then used to identify the parameters used in equation 2 that capture the weight of each layer $\omega^H = \omega^W = \omega^S = 22\%$, $\omega^P = 4\%$ and $\omega^C = \omega^N = 10\%$.

The final column of Table 4 reports the potential pool of contacts for those layers where the actual contacts are drawn randomly every day. This information is not available in Mossong et al. (2008), however it is an important determinant of the spread of infection, and therefore we pin it down using the network structure, as well as additional information. For the shopping links, every person does (on average) $2v_{H1}$ and $2(1-v_{H1})$ shopping trips to the small and large establishments, respectively. When shopping at the local mom and pop store, the pool of potential sales people that a shopper meets is given by 4 (the employment size of the H-small establishment). When shopping at large establishments, the pool of potential contacts is given by $\tilde{v}M$, with $\tilde{v} = (1 - v_K)(1 - v_{H1})$, which is the total number of workers that work in large establishments in the H-sector. Note that pool of contacts (i.e. potential sales people) when shopping at large establishments is much larger than the contacts when shopping at the small stores. The reason is the assumption of a different customer base: when shopping at a small establishment, a person always visits the same local store whereas when shopping at a large establishment, the individual is randomly assigned to an establishment in the city.

For adults working in local small establishments in the H-sector, the pool of potential customers is given by the local customer base which is equal to the size of the population divided by the number of workers in the small establishments, $\frac{M}{M(1-v_K)v_H v_{H1}} \simeq 56$. Workers in large establishments in the H sector draw their potential customers from the whole city, so their pool of contacts is the city population M.

For public transportation, we choose the number of potential contacts equal to 54 to match the seating capacity of the R160 New York City subway car. Finally, for schools, we proxy the pool of potential contacts with the class, so we set the size of the pool to 26 to match average class size (across grades) in New York City public schools for 2018-19. The ratio between the actual contacts and the contact pool for the unstable layers (shopping, public transportation, school and H-work place) is then used to set the Bernoulli parameter ρ_i in the network clocks described in Equation 1.

4.5 Disease Transmission

The final parameters to be determined are those regulating the diffusion of the disease, described in Sub-Section 3.2. We set some parameters based on epidemiological studies on COVID-19, and set the remaining, for which there is less evidence, to match the early stages of infection diffusion in the New York metro. Parameters are reported in Table 5.

Starting on the symptomatic branch, we set γ to 0.25 and ρ_S to 0.071, in order to match a duration of the pre-symptomatic and symptomatic stages of the disease to 4 and 14 days respectively (see, among others, Guan et al. 2020). Going now to the asymptomatic branch, we follow Li et al. (2020) and set η to 0.5, capturing the finding that asymptomatic are half as infectious as the patients showing symptoms. Also, following Li et al. (2020), we set ρ_A to match a duration of the asymptomatic stage to 4 days. The three remaining parameters are π, the infectiousness of the symptomatic cases, α, the fraction of exposed that transit to the asymptomatic stage, and r_{as}, the initial ratio of asymptomatic to symptomatic. Our

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strategy is to pick these parameters so that the infection curve in the model exactly matches the data in the initial period of the infection. In the next section we explain in more detail this choice.

Table 5: Disease Transmission Parameters

Parameter Name	Symbol	Value	Target
Infection Probability	π	0.52	Calibrated (see text)
Relative Infectiousness of IA	η	0.50	Li et al. (2020)
Prob. of transition from E to IA	α	0.6	Calibrated (see text)
Initial Ratio of Asy. to Sym.	r_{as}	1.7	Calibrated (see text)
Prob. of transition from IP to IS	γ	0.25	Incubation 4 days
Prob. of transition from IS to R	ρ_S	0.071	Duration of disease 14 days
Prob. of transition from IA to R	ρ_A	0.25	Duration of asymptomatic stage of 4 days

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5 Results

This section first describes how we use mobility data to discipline changes in the network contacts during the pandemic. It then shows how the calibrated ECON-EPI network performs in explaining the infection dynamics, and contrasts it with another popular model of infection spreading, i.e. the standard random mixing SIR model. Lastly it discusses the contribution of the different layers of the network to the progression of the disease.

5.1 Changes in network structure during the pandemic

We focus on the period from March 8th, 2020, where the first 160 cases where reported in the New York metro area, until May 25th, 2020. We start our model city with the same number of infected symptomatic per million in the New York MSA on March 8th. The progress of the infection in the model does not only depend on initial conditions and epidemiological parameters, but also on the network structure which, as the pandemic spreads, evolves. In order to capture this evolution we use both information on actual regulatory changes and data on mobility, as reported by Google.[15] In particular Google reports three mobility series that track the visits and length of stay of individuals at workplaces, retail and residences. These series have a natural mapping into our model: workplace mobility maps into presence of L-workers at their establishments, retail mobility maps into presence of workers and shoppers at H-establishments and finally residential mobility captures the time individuals spend at home. These three measures for New York City are reported in the top panel of Figure 5. The panel shows that initially workplace/retail mobility sharply falls, then it stays constant at a depressed level and partially recovers towards the end of the period. Residential mobility displays the opposite pattern. This evolution is most likely the result of both changes in policy and in behavior. Our strategy is to match this evolution by furloughing a time varying fraction of both L and H workers. In particular in each period we match the observed decline in workplace mobility in two ways. In the first days of the pandemic we match the decline in workplace mobility by having all L-workers that can work from home starting to do so. As time progresses and workplace mobility continues to decline we match the further decline by furloughing a fraction of L-workers each day. Then we furlough a fraction of H-workers each day so to match the decline in retail mobility. We impose a larger percentage decline of the employment in large H-establishments, relative to small ones, to be consistent with the fact that authorities in New York shut down events with more than 500 attendees by March 12th.

When a worker is furloughed, her time is reallocated to their household and neighborhood networks. A fraction of the work hours are assigned to the household and neighborhood layer so that the increase in home hours matches the increase in residential mobility. Note that when we furlough H-workers we also cut a number of shopping links, as shoppers assigned to furloughed workers are not able to shop. We also close schools in the model on March 14th, which is the date in which K-12 schools are shut-down statewide.[16]

The mobility patterns suggest a division of our period in three subperiods. The first (labeled "closing", from March 8th to April 3rd) is the period in which mobility sharply declines, the second (labeled "lock-down", from April 3rd to April 26th) is the period in which mobility stays low, and the last (labeled "re-opening", from April 26th to May 25th) when mobility picks up.

[15]See appendix A for a timeline of the pandemic related policies in New York.

[16]Schools were announced to be closed on March 16th, a Monday, so we shut down schools effectively on Friday 14th.

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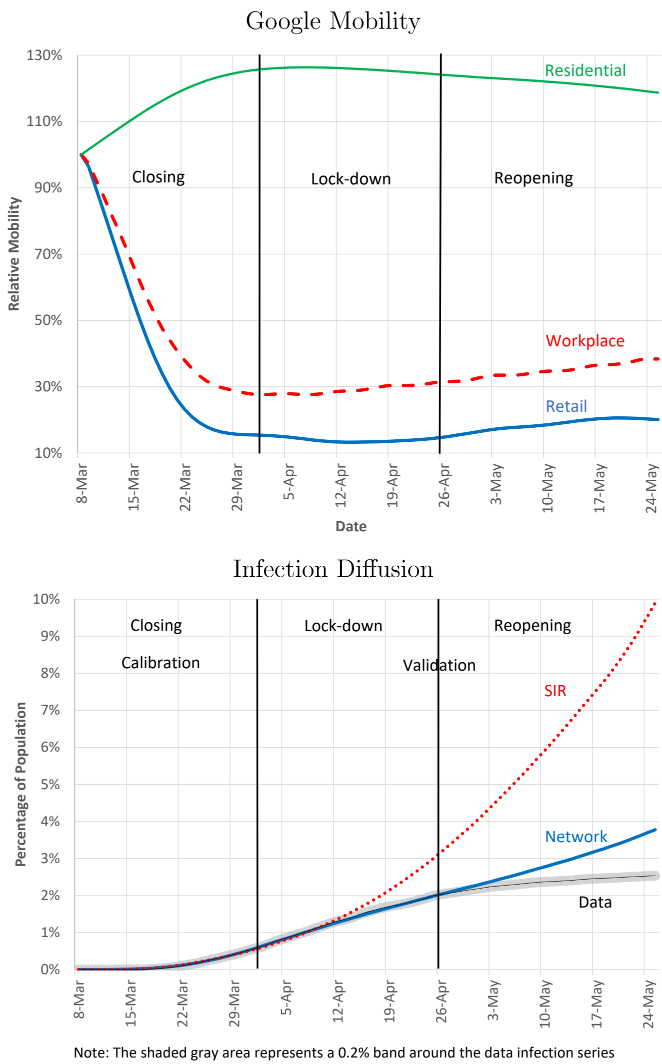

Figure 5: Network v/s SIR

5.2 Network v/s SIR

The bottom panel of Figure 5 shows the cumulative infection curve generated by the network model against the data. Since our calibration strategy is to pick the epidemiological parameters π, α, and r_{as} to match the infection curve in the first sub period, the network model and the data lie on top of each other by construction until April 3rd. The periods after April 3rd, however, constitute a validation of the model. The network model is close to the empirical epidemiological curve all throughout the lock-down phase, and shows more growth in infection (relative to the data) as the city starts to re-open. For comparison purposes, we also report the infection curve predicted by a standard SIR model, where each individual has the same number of contacts as in the network, but the contacts are randomly drawn across the entire population.[17] We calibrate the epidemiological parameters in the SIR in order to match the data infection curve in the first sub-period (exactly as we did for the network model), and we change the number of random contacts in the SIR so to match the average change in Google mobility. Possibly the most important message of Figure 5 is that even when the two models (Network and SIR) are put on equal footing, as they generate the same initial surge of infection and have similar containment measures, they have sharply different predictions for the evolution of the pandemic. In the network model, the infection naturally slows down, as the reduction in the number of contacts is enough to keep the infection local and prevent the disease from reaching the entire population. The SIR model, however, predicts that despite the reduction in contacts, the infection takes off in an exponential fashion. This is due to the random nature of contacts: in the SIR model, an individual is equally likely to meet any other individual in the city, whereas in the network model contacts are more clustered and less random. Before we move on to policy experiments, we use our calibrated model to quantify the contribution of several layers to the infection.

5.3 Infection Decomposition and Complementarities

In this section, we study the effect of shutting down different layers of the network, and how this shutdown interacts with the transmissibility of the disease. In order to do so, we sequentially set to 0 the weights of each layer of the network, and assess the impact of shutting down one single layer on the evolution of the infection. An important issue in assessing the impact of a given layer is the presence of mitigation policies (for example school

[17]We do not directly use the SIR model, but an equivalent network formulation. Rather than have multiple network layers, each individual has a single layer which connects them to all other nodes. The transition between health states is regulated by the same parameters as in the network model, and described in Figure 3. The probability of infection is therefore determined by the epidemiological parameters π and η and the per-period number of contacts. The pre-pandemic number of contacts is set to the average number of contacts across children and adults reported in Mossong et al. (2008), and each period this number is adjusted to match the average change in the Google mobility reports. The parameters π, r_{as}, and α are then calibrated to match the early stages of the pandemic, and take on values 0.48, 1.69 and 0.63, respectively.

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closures) or endogenous reduction of contacts (as captured by Google mobility). If contacts in a layer are already substantially reduced, we might find that shutting down that layer completely does not have much impact on infection; this, obviously, does not reflect the importance of the layer, but rather the fact that the layer was already almost closed. For this reason, we conduct this experiment in the fully open (pre-pandemic) network.

Figure 6 shows the evolution of the disease under different scenarios. In both panels, we show epidemic curves for the network with all layers open (benchmark), with the large H-establishments shut down, with the L-establishments shut down and finally with schools shut down.[18] The panel on the left uses the infection probability parameter π from our benchmark calibration, while the right panel plots the same curves with a lower infection probability parameter, which we use later in our re-opening experiments.

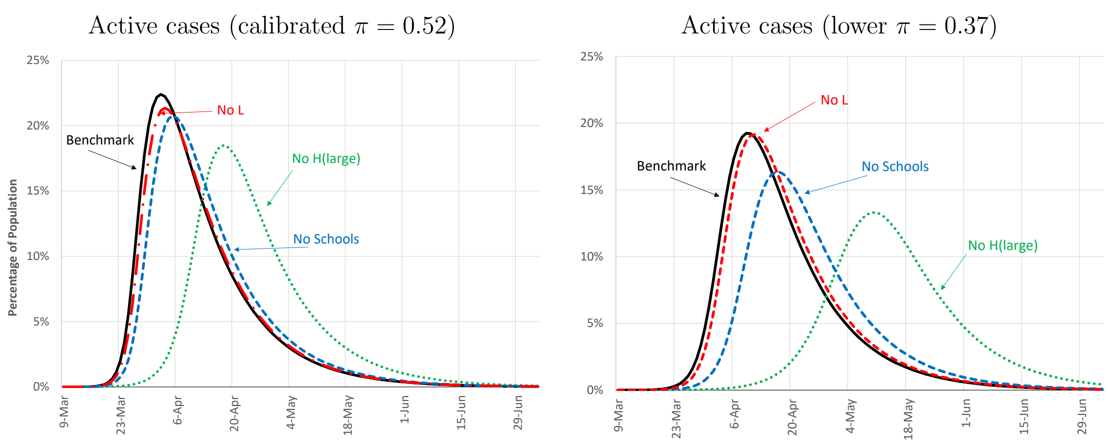

Figure 6: Infection Decomposition

Both panels show that the component of the network which has the biggest impact on infections is the large H-establishments. Shutting those establishments down achieves a substantial delay in the peak of the infection curve and a substantial reduction in the total number of infections. There are two reasons for this. The first one is that, as shown in Table 4, workers in the large establishments in the H-sector have the highest number of contacts,

[18] We do not plot curves for public transportation, and small H-establishments as they have a very small impact.

so they are obviously more likely to get sick and spread the infection. The second one is that the customers these workers interact with are randomly drawn from the entire city; this makes their layer very close to a random mixing set-up, and thus very conducive to a rapid spread of the disease. Another layer that is quantitatively relevant is the one related to schools. Table 4 shows that kids in schools have a high number of contacts, also randomly drawn, albeit from a smaller set.

We find it interesting to compare the right and the left panel of Figure 6. The curves in the right panel are drawn from a simulation with a smaller infection probability parameter and thus, not surprisingly, are lower, as there is less infection spreading. Note however that with a smaller π the impact of shutting down high contact layers gets magnified. To see why, consider the infection probability of a susceptible node with many infected contacts. If π is close to 1, the infection probability is close to 1 and not very sensitive to a marginal reduction of contacts. In this case, shutting down a layer (and thus reducing the number of contacts) does not affect much infection dynamics, which is always very fast. On the other hand, when π is lower (but sufficiently far from 0), Equation 3 implies that a marginal reduction of contacts can significantly reduce the infection probability. Therefore, in this case infection dynamics are more sensitive to the network structure, and mitigation policies that reduce the number of contacts are more effective. This highlights an important point, namely the *complementarity* between mitigation policies that reduce the transmission of the disease (e.g. face masks) and mitigation policies that reduce the number of contacts (i.e. shutting down malls). If the transmissibility of the disease is high (π close to 1), then a moderate reduction in contacts is not very effective in reducing infections. Similarly, if individuals have a large number of contacts, a moderate reduction in transmissibility is not effective. However, if the transmissibility is lower, then the same reduction of contacts can have a large impact on the spread of the disease, and similarly if the number of contacts is lower, the same reduction in the transmissibility of the disease can have a large impact on infection levels. We will return to these considerations later when we analyze re-opening strategies.

Having established that the network model constitutes a good benchmark to study the evolution of the pandemic, and having analyzed the importance of various layers, we now use the model to conduct two types of policy experiments. The first set, in Section 6.1, studies how counterfactual policies would have affected ECON-EPI outcomes at the outbreak of the COVID-19 pandemic in New York City. These experiments are also helpful to evaluate different options, should a second wave of infections hit. The second set of experiments, in Section 6.2, studies different strategies for reopening the city, as the infection subsides.

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6 Policy Experiments

6.1 Lock-down strategies

As Figure 5 shows, after the draconian lockdown of March and April, infections in the New York metro area stopped increasing by mid May. The question that is often asked is whether the lock-down was too strict. To answer this question, we perform a series of experiments that relax lock-down restrictions in the first four weeks of the pandemic (e.g., between March 8th and April 5th). With the lessons drawn from these experiments, we design a counterfactual *smart* mitigation policy that targets sectors with higher risk of spreading. We show that this policy could have reduced infections and increased output relative to the benchmark case.

We start from our benchmark case and compare it with three counterfactuals in which we gradually bring back the same number of shutdown workers in each sector (L, H-small, and H-large).[19] We then compare the epidemiological and economic outcomes to our benchmark case. Starting with the epidemiological outcomes (the top panel), we see that increasing workers in the H-large sector has a very large impact (over 1.5% of the population) on infections. Extra workers in the H-small sector have a moderate impact (0.5% of population), while extra workers in the L-sector have almost no impact on the level of infections. The large increase in infections brought about by the additional H-large workers is not surprising; as discussed earlier, these workers have a lot of random contacts, thus they function as spreaders. The sizeable increase in infection coming from bringing back workers in the H-small establishments is more surprising. As discussed in Section 5.3, shutting down these workers when the whole economy is open has no impact on infection dynamics. The reason for this difference is the starting point of the experiment. Adding H-small workers when the economy is substantially shutdown contributes to the spreading, while the marginal contribution of the H-small workers when the economy is fully open is small. Finally, the L-workers constitute highly clustered groups in their respective productive units, who meet frequently and do not interact with customers. For these reasons, a relatively small increase in the number of these workers does not affect infections on the margin.

Moving now to the economic outcomes (the bottom panel), we first observe that the largest output gain (around 2% of GDP) is obtained by adding the H-large workers, followed by an output gain of 1.5% of GDP, obtained by adding L-workers; the smallest output gain (around 1%) is obtained by bringing back the H-small workers. To understand this ranking

[19] The increase in the amount of workers in each sector is around 1% of the pre-pandemic total employment.

consider that the marginal productivity of a worker is increasing in the capital-labor ratio of the worker's sector. In the pre-pandemic equilibrium the capital-labor ratio for the L-workers is higher than the one of H-workers (regardless of the size of the establishment). During the pandemic however, workers in the H-large sector are mostly shutdown, implying that their capital-output ratio is the highest: that explains why bringing them back gives the highest output gain. L-workers and H-small workers are instead shutdown in roughly the same proportion, and therefore, because L-workers have a higher capital to start with, bringing them back results in a larger gain (relative to the H-small).

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The results so far suggest that tightening the shutdown in the H-sector while relaxing it in the L-sector might achieve a reduction in infection *and* an increase in output, relative to the benchmark. In Figure 8, we consider the effect of such a policy, which we label smart mitigation. More specifically, we impose stricter lock-down measures in the H-sector (mostly in the H-small sector) while relaxing those in the L-sector. We impose that the total number of individuals going to work is the same as the benchmark and that the amount of workers in each sector affected by the policy is around 1% of the pre-pandemic employment level (the same amount considered in the experiments in Figure 7). A concrete example of such a policy would be to allow more workers in manufacturing plants to go to work, while furloughing an equal number of retail workers that are allowed to go to work in the benchmark. The figure shows that the smart mitigation achieves a substantial double-gain. The top panel shows that it reduces the number of infections by 1.5% of the population of the metro area (300 thousands fewer cases) and the bottom panel shows that at the same time it increases output, relative to the benchmark, by an average of 1%.

To better understand the source of the double gain one can view this policy as a two steps procedure. The first step is to add workers to the L-sector. As Figure 7 shows, this step involves an increase in output and virtually no change in infection levels. The second step involves a reduction of (mostly) H-small workers. Figure 7 suggests that this causes a substantial reduction in infection and a reduction in output that is smaller than the gain obtained in the first step: hence the double gain.

6.2 Re-opening strategies

Results in Section 5 suggest that the network model captures well infection dynamics in the lock-down period. However, as the city starts to reopen in the month of May, the

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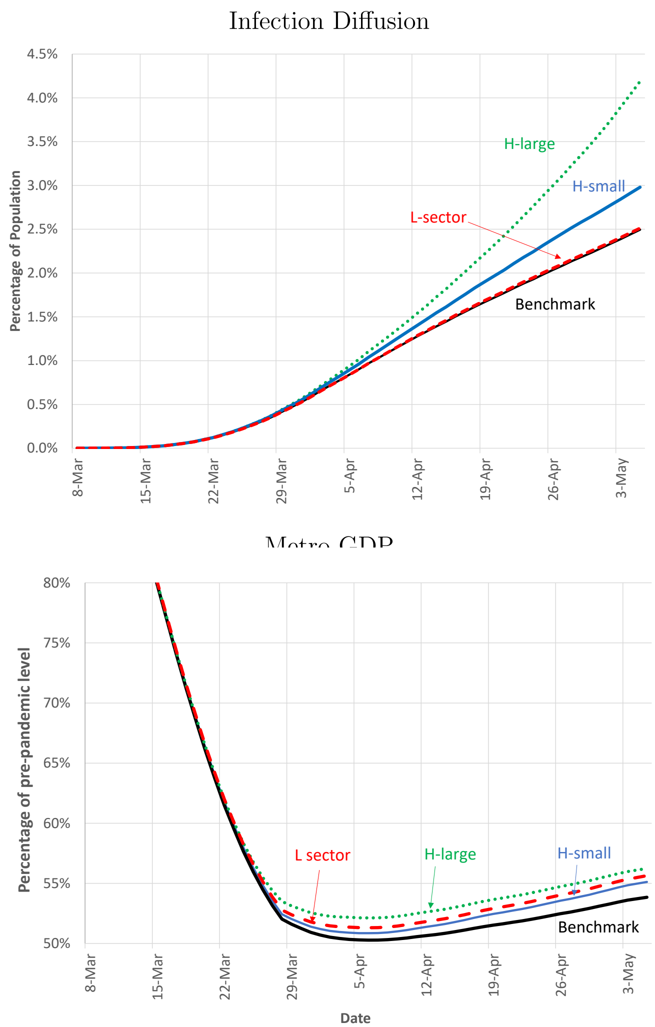

Figure 7: Policy counterfactual

model predicts a level of infection that is higher than the data. One possible reason for this discrepancy is that we keep the epidemiological parameters constant throughout our period, while the much broader availability of PPE and of testing, together with social distancing (e.g. requiring individuals to be 6 feet apart form each other) has reduced the transmissibility of the disease. As this issue is critical to analyze reopening scenarios, we incorporate changes in transmissibility by assuming that in the post lock down period (after April 26th) there is

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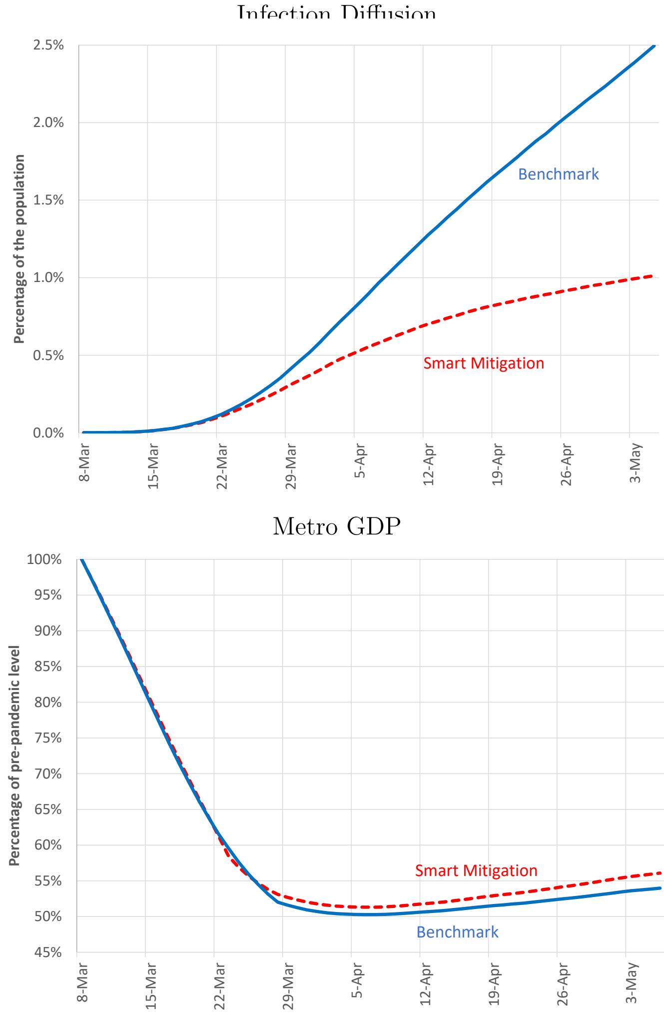

Figure 8: Smart Mitigation

a one-time decline in the parameter π. We calibrate this decline (from 0.52 to 0.37,) so that the infection curve in the reopening period (April 26th through May 25th) matches the data. The result of this procedure is illustrated in Figure 9. The figure suggests that the network model with the recalibrated π can be a good starting point to study reopening strategies, that is to predict the evolution of infection and output under different assumptions for the evolution of mobility.

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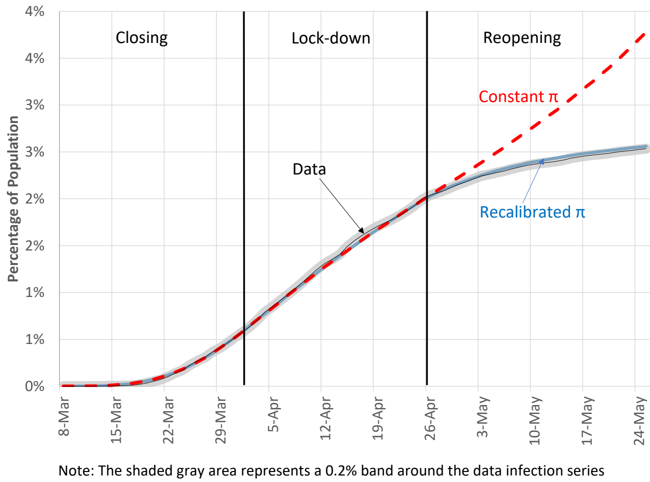

Figure 9: The impact of lower π

6.3 Re-opening workplaces

In Figure 10 we consider three scenarios for the New York metro. The first (labeled no-reopening) is the one in which mobility stops increasing on May 25th. The second (labeled L-reopening) is the one in which only the L-establishments are allowed to substantially reopen, and the third (labeled H and L reopening) is the one in which both L and large H-establishments are allowed to substantially reopen.[20] The top panel depicts the infection curves, while the bottom panel shows metro GDP. Under the no-reopening scenario GDP remains severely depressed; on the positive side, the cumulative infection curve becomes flat, suggesting that a prolonged shutdown can stop the growth of the disease and thus eradicate it. The dashed lines show that a substantial reopening of the L-sector comes at virtually no infection cost, and with large GDP gains, as the metro area GDP would recover almost up to 25% of the pre-pandemic level. Finally the dotted lines, displaying the consequences of a reopening of both the L and large H-sector, suggest that this scenario is potentially troublesome. GDP would recover more substantially, but the city would suffer a dramatic second wave, with the total number of infected reaching over 7% of the population by early September. It is doubtful whether in such a scenario the GDP recovery can be sustained.

[20] Across the three experiments the reopening pattern of the small H-establishments is kept constant, and schools are kept closed.

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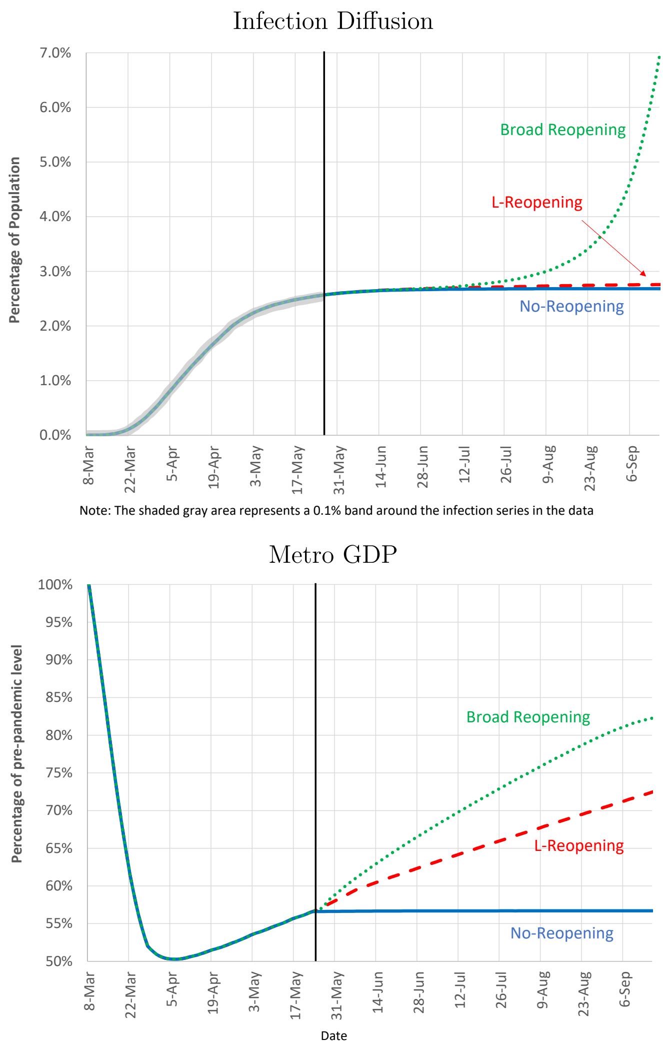

Figure 10: Reopening scenarios

6.4 Reopening schools

In the experiments above, we assumed that schools remained closed until the end of the year. One important issue during the COVID-19 pandemic is the impact of reopening activities for the kids, such as schools and summer camps. The impact of reopening these activities on infections depends significantly on the current level of infections, and hence on the date in which the reopening happens. In the top panel of Figure 11, we depict the effects of school reopenings in different dates assuming that mobility in the L and H sectors stays constant at the level of May 25th. On the right scale of the panel, we plot the curve depicting the level of active cases under the scenario of no-reopening of schools. This curve shows that in July, there is still a positive mass of active cases; thus if schools were to re-open in July the large increase in contacts brought about by the open schools would imply a fast growth of symptomatic infections which would reach 10% of the population by mid November. If, on the other hand, schools were to re-open in August, when the mass of active cases is minimal, the addition of contacts from schools would not be causing a rapid takeoff of infections, so the disease would be manageable.

In our final experiment, we consider reopening scenarios that combine increases in mobility of the L-sector (such as those in Figure 10) with school reopenings. We consider two scenarios: the benchmark case in which schools reopen with the normal number of contacts, and a socially distanced scenario where contacts are reduced to 2 per kid. We assume that schools open on August 1st, and that school-related activities end by Thanksgiving day. The progression of infections is shown in the bottom panel of Figure 11. The key result is that, even in the case of strongly socially distanced schools, the infection takes off rapidly and exceeds 5% of the population by November. This happens because the impact of reopening the L-sector, despite being fairly modest in itself, is sufficient to keep the number of active cases high enough, so that when schools re-open in August (and the L-sector remains open) infections take off. This experiment highlights the importance of interactions among social layers in our network. Reopening just the L-sector or just schools (in August) results in a relatively small increase in infections, but opening both simultaneously results in a distinctive second wave during the Fall. These experiments also confirm the point in Section 5.3 about the importance of limiting contacts even when the transmissibility of the disease is lower. All the reopening exercises are done with a lower transmissibility parameter π, and they all show that a relatively small change in the number of contacts can change the pattern of the disease from eradication to fast diffusion. Besides the complementarity in infection there could be another important complementarity between schools and work, since, when schools are closed, parents have reduced ability to go to work. So far we have abstracted from this issue, but we conjecture that modeling it explicitly would make a stronger case for an early shutdown that would allow schools to re-open.[21]

[21] For an interesting analysis of the effect of school closing on work choices of men and women see Alon et al. (2020).

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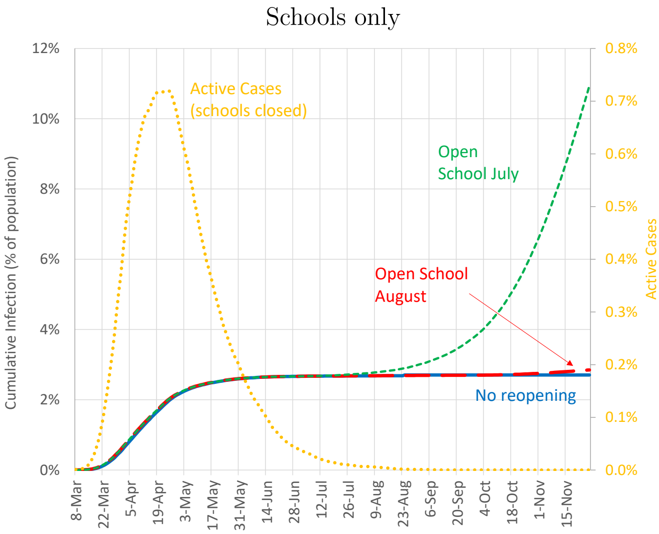

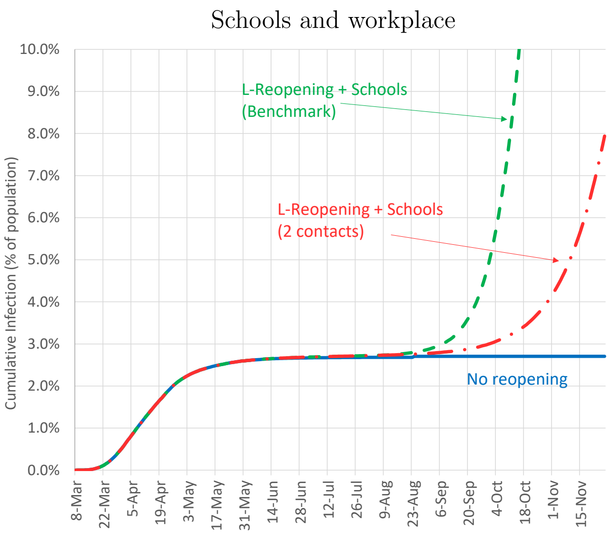

Figure 11: Reopening Schools

7 Conclusion

We develop an ECON-EPI network model to study the impact of the COVID-19 pandemic on a large US metro area, and to evaluate policies that limit the human as well as the economic damage. We build on the traditional SIR model by using network theory to put

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structure on the patterns of human interactions. We find that this structure is useful to understand observed epidemiological curves, featuring a large initial surge and a plateau at a relatively low level of infections. Moreover we use our set-up to quantify how layers of interactions contribute both to infection levels and economic activity. Network layers that feature numerous and unstable contacts (such as large gatherings or schools) work as ignition rods for the infection. Smart lock-down policies shut down these layers early, and smart reopenings keep them closed for longer. Opening sectors where workers interact with each other in stable teams (such as manufacturing) is the best strategy to minimize output losses, while at the same time keeping the spread of the disease under control.

There are several directions in which we could expand the study of pandemic control on ECON-EPI networks. In our framework interactions are, for the most part, exogenously determined. One direction for further research would be to study how the ECON-EPI pattern of contacts can change endogenously, both in the short run, in response to fear, and in the long run, in response to increased risk of a new pandemic.[22]

Our network analysis can also prove useful to think about how to efficiently allocate limited testing resources. The same principles we used to design "smart" lockdown and reopening policies, can be used to design "smart" testing. We conjecture that it would be efficient to allocate testing to layers of the network which have more numerous and more unstable contacts, and our framework could be used to quantify the effects of such a policy.[23] Another extension of our analysis would be to introduce more group level heterogeneity, such as different communities/neighborhoods in the city. Such an extension would help to understand how much of the observed large differences in disease outcomes across groups can be explained by differences in their social structure.[24] It could also help to design social policies that protect the more exposed communities and, at the same time, reduce average spread. Finally, a related application of our analysis would be to analyze how much of the differences in epidemiological and economic outcomes across metro areas and across countries can be explained by differences in the network of interactions.

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[22]See the recent literature on the COVID-19 pandemic studying behavioral responses to the infection, such as Alfaro et al. (2020), Farboodi et al. (2020), Krueger et al. (2020) and Toxvaerd (2020). See Fogli and Veldkamp (2020) for a study of the endogenous evolution of network of interaction in societies with difference prevalence of diseases.

[23]For some early works on efficient testing using the standard SIR set-up see Berger et al. (2020) and Chari et al. (2020).

[24]For evidence of local differences in disease outcomes in the New York metro see Almagro and Orane-Hutchinson (2020).

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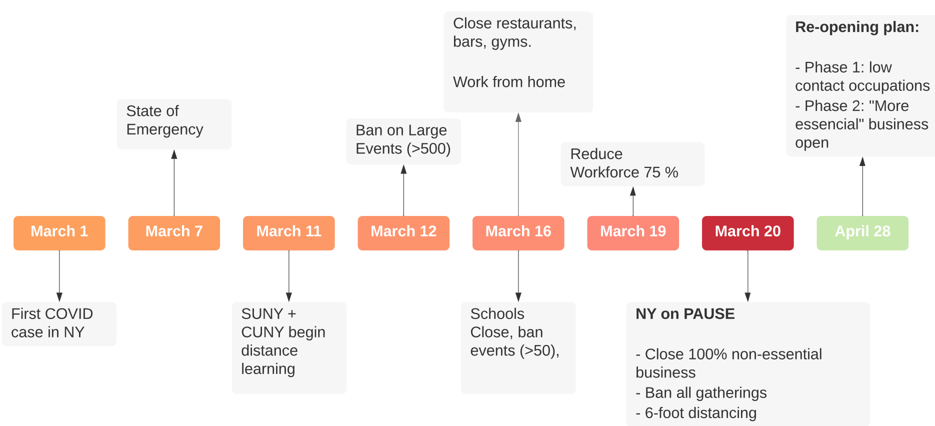

Figure 12: Timeline of lock-down Policies

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The Optimal Allocation of Covid-19 Vaccines

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Covid-19 vaccine prioritization is key if the initial supply of the vaccine is limited. A consensus is emerging to first prioritize populations facing a high risk of severe illness in high-exposure occupations. The challenge is assigning priorities next among high-risk populations in low-exposure occupations and those that are young and healthy but work in high-exposure occupations. We estimate occupation-based infection risks and use age-based infection fatality rates in a model to assign priorities over populations with different occupations and ages. Among others, we find that 50-year-old food-processing workers and 60-year-old financial advisors are equally prioritized. Our model suggests a vaccine distribution that emphasizes age-based mortality risk more than occupation-based exposure risk. Designating some occupations as essential does not affect the optimal vaccine allocation unless a stay-at-home order is also in effect. Even with vaccines allocated optimally, 1.37% of the employed workforce is still expected to be infected with the virus until the vaccine becomes widely available, provided the vaccine is 50% effective, and assuming a supply of 60mil doses.

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The ongoing severe acute respiratory syndrome–coronavirus 2 (SARS-CoV-2) pandemic has claimed over 750,000 lives worldwide as of August 12th, 2020, and paralyzed economic activity around the globe for extended periods. Vaccination is seen as the principal strategy for containing the pandemic. However, even though vaccines are being developed at historical speed, they are expected to be initially in limited supply (Cohen, 2020). A crucial question stands: who will get first access to a vaccine when one becomes available? Currently, principles used for pandemic influenza vaccination under limited resources have been informing the deliberations of the Advisory Committee on Immunization Practices (ACIP) concerning Covid-19 vaccination. However, the characteristics of Sars-Cov-2 are markedly different than those of influenza, and new vaccine distribution protocols are necessary.

While there is little disagreement that high-risk individuals in high-exposure occupations, such as front-line healthcare workers, should be included in the initial priority group for vaccination, assigning priorities over other groups remains subject to debate. To start with, a disproportionate toll on the elderly suggests that age should be the primary consideration. However, infection clusters arising in hospitals and meatpacking plants indicate that there are occupations in which the risk of exposure to the virus is substantially raised. Deciding whether to prioritize meatpacking plant workers over elderly citizens must factor in the ages of the workers and the occupations of the elderly.

Moreover, the coronavirus pandemic is unique in its wide-spread impact on economic activity. Non-pharmaceutical interventions, such as social distancing and stay-at-home orders, have been implemented on an unprecedented scale. While many countries are relaxing constraints, lockdowns are expected to be imposed again if the virus re-surges. Thus, vaccines perhaps should be allocated not only based on the risk of infection or death but also based on the economic benefits of allowing certain groups of people to return to their workplaces earlier than others.

We develop and estimate a model to evaluate vaccination allocation strategies. We recognize that people face different levels of infection risks depending on their occupations and that, conditional on being infected, the risk of death depends on their ages. The vaccine is assumed to be effective only to some extent and in limited supply relative to the entire population. A vaccine distribution strategy may be supplemented by a targeted stay-at-home order that prevents certain age-occupation groups from returning to their workplaces at an economical cost.

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We solve a simple linear-program that takes into account the cost that an individual expects to incur if infected and the economic benefit from going back to her workplace. Our procedure allows us to derive the optimal vaccine distribution among all allocations based on occupation and age. This enables us to address who should get the vaccine first: young meatpacking plant workers or elderly school teachers?

To assign priorities over populations with different occupations and ages, we estimate occupation-based exposure risks (i.e., infection rates), and use estimates of age-based infection mortality rates. The infection mortality rates vary across ages far more than the estimated infection rates across occupations. Accordingly, our model suggests a vaccine distribution that emphasizes age-based mortality risk more than occupation-based exposure risk. This insight is robust to supplementing the vaccine distribution with a stay-at-home mandate for targeted occupation and age groups. If we consider a specification in which some occupations can be done from home, then the vaccine can be distributed to younger individuals who need to return to their workplaces. However, if the supply of the vaccine is scarcer, occupation-based exposure risks become more relevant as we distribute vaccines to individuals in relatively lower-risk occupations only at very advanced ages.

Our model implies that, even when vaccines are allocated optimally, 1.37% of the employed workforce is still expected to be infected until the vaccine becomes widely available, provided the vaccine is 50% effective and assuming a supply of 60mil doses. Either increasing the effectiveness of the vaccine or increasing the vaccine supply while keeping the effectiveness constant decreases the proportion of people infected with the virus. To curb the coronavirus-related deaths to a level comparable to seasonal flu the optimal vaccine distribution will take into account even more age-based mortality rates rather than occupational risks, and a more stringent stay-at-home order is inevitable.

The allocation of scarce resources, including vaccines, during a pandemic has also been discussed by Pathak et al. (2020). While Pathak et al. (2020) studies the implementation of a given proportional prioritization (i.e. vaccine reserves for different groups), we focus on which groups to prioritize. To illustrate, if the population is partitioned in healthcare vs. non-healthcare workers, and old vs. young, our model assigns priorities among young healthcare workers and elderly non-healthcare workers, based on occupation-related exposure and age-based infection mortality. In contrast, Pathak et al. (2020) study how to implement the distribution of a limited supply of doses,

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if a fraction is reserved for healthcare workers, and the remaining for the elderly. While the implementation is not trivial as some healthcare workers are also elderly,[1] their model is silent about how the reserves across the two groups should be decided.

1 The Model

We develop a simple model to identify priority groups for vaccination based on occupations and ages. For this, we partition the population into groups by occupations and ages. In particular, our environment consists of the set of occupations I, the set of age-groups J, and the population distribution over occupations and age-groups $P \in \mathbb{R}_+^{I \times J}$. Hence, each element p_{ij} denotes the number of people with certain occupation i and in an age-group j. Each person in occupation i faces a risk of infection denoted by r_i. Associated with each person in an age-group j is a cost of infection c_j.

A policy consists of a distribution of a limited supply of vaccines and a targeted stay-at-home order. A vaccine distribution $V \in \mathbb{R}_+^{I \times J}$ with v_{ij} represents the number of people in occupation i and age-group j that receive a vaccine. The vaccine distribution satisfies a supply-side budget constraint $\sum_{i,j} v_{ij} \leq b$, where b represents the quantity of vaccine initially available, and it is assumed to be less than the total population $\sum_{ij} p_{ij}$. The vaccine allocation policy can be supplemented by a targeted stay-at-home order $H \in \mathbb{R}_+^{I \times J}$ with h_{ij} representing the number of people in occupation i and age-group j that cannot return to their workplace. Overall, $V + H \leq P$.

A vaccine recipient becomes immune to the virus with probability γ, which captures the vaccine's effectiveness. Hence, the policy can reduce the number of exposed populations by $\gamma V + H$ across different occupations and age groups. For each group (i, j), the policy prevents a certain population to be exposed to infection by the virus and saves costs by $(\gamma v_{ij} + h_{ij}) r_i c_j$.

The stay-at-home policy H comes with the suspension of economic activities. Let $F \in \mathbb{R}_+^{I \times J}$ denote the values of economic activities that accrue to individuals. In particular, each f_{ij} denotes the value of the economic activity i undertaken by an individual in the age-group j. Thus, the total loss in value from stay-at-home for the group (i, j) is $f_{ij} h_{ij}$, unless the occupation i can be worked at home, which we allow in one of our specifications.

[1] For example, an elderly-first implementation favors, ironically, healthcare workers. Elderly healthcare workers receive vaccines based on their age rather than on their occupations, and this way extra vaccines are available to younger healthcare workers. Hence, healthcare workers can receive vaccines in excess of the doses reserved for them.

The goal is to find a policy (V, H) that minimizes the loss of lives and the economic burden from a stay-at-home order. In particular, the planner solves the following linear program:

$$
\begin{aligned}
(\text{LP}; \gamma, b, \theta) \quad & \min_{V,H} \sum_{i,j} (\gamma v_{ij} + h_{ij}) r_i c_j - f_{ij} h_{ij} \\
& \text{subject to} \\
& (i) \sum_{i,j} v_{ij} \leq b, \quad \text{(budget constraint)} \\
& (ii) v_{ij} + h_{ij} \leq p_{ij} \quad \text{(feasibility)} \\
& (iii) \sum_{i,j} r_i d_j (p_{ij} - \gamma v_{ij} - h_{ij}) \leq \theta \sum_{i,j} p_{ij}, \quad \text{(measured fatalities)}
\end{aligned}
$$

where d_j is the infection fatality rate rate that an individual in age group j faces. Constraint (iii) in this program allows us to derive the optimal policy (V, H) such that the (unconditional) fatality rate expected to occur in the population is capped, given a vaccine effectiveness of γ. Alternatively, constraint (iii) can inform us about the minimum vaccine effectiveness required to cap the (unconditional) fatality rate at θ, if a stay-at-home order is not possible. Depending on the values assumed for the parameter θ, constraint (iii) need not be binding.

2 Data and Estimation Strategy

We track 8 age-groups for the 2017 U.S. population, 16-19, 20-29, 30-39,..., and 80+, distributed over 454 occupations, aggregated at the 4-digit Census OCC code. We obtain the number of people for each age-group employed in a given occupation from the 2017 American Community Survey (ACS). Our sample is representative of 60% of the U.S. population.

To proxy for the benefit, f_{ij}, that an individual in age group j generates from participating in economic activity by occupation i, we use the average yearly wage for each age group and occupation, also provided by the 2017 ACS. From an economics perspective, the wage captures a worker's contribution to the production of total output as measured by GDP, or equivalently the GDP loss if a worker is unable to work due to a stay-at-home order (Hulten, 1978, Baqaee et al., 2020).

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Table 1: The Value of Statistical Life (VSL) and Infection Fatality Rate by age-groups.

Age group	EU population	Infection fatality rate (%)	VSL in mil. USD	The cost of infection in USD
< 19	0.215	0.001	15.3	153
20-29	0.12	0.005	16.1	805
30-39	0.135	0.02	15.8	3,160
40-49	0.14	0.05	13.8	6,900
50-59	0.135	0.2	10.3	20,600
60-69	0.115	0.7	6.7	46,900
70-79	0.09	1.9	3.7	70,300
80+	0.05	8.3	1.5	124,500

Note: for the age group 16-19, we used VSL of the ages 10-19.

The average cost, c_j, for a person in age-group j that has been infected with the virus depends on the infection fatality rate, d_j, that her age group faces and on the value of statistical life (VSL) for her age group. In particular, the cost of infection is given by

$$c_j = d_j \times \text{Value of statistical life}_j.$$

For the infection fatality rate – the number of deceased among the infected people – we use the estimates provided by Salje et al. (2020) who jointly analyze French hospital data with the results of a detailed outbreak investigation aboard the Diamond Princess cruise ship.[2] For the VSL, we use the estimates provided by Greenstone and Nigam (2020) who update the estimates of Murphy and Topel (2006) to 2015. The details are reported in Table 1.

The remaining variable that we need to estimate in the model is the infection rate, r_i, associated with each occupation i, for which the data is not directly available. To circumvent the lack of data, we proceed in two steps. First, we infer the infection rate for each occupation group based on the coronavirus-related deaths by occupation that have occurred between March 9th and May 25th, 2020, as reported by the U.K. Office for National Statistics (ONS). ONS reports the age-standardized death rate per 100,000 of each minor occupation i by gender. This death rate is unconditional on infection and based on the 2013 E.U. standard population distribution. We use the employment-weighted average of the death rates by gender and construct the death rate, D_i, per 100,000 people for each U.K. minor occupation. Given the infection fatality rate, d_j, for age group

[2] In a separate robustness exercise (Fig. S.6 and Table S.2) we also use the reported infection fatality rate data from South Korea, which has a very accurate track-and-trace system. Among non-elderly workers, the infection fatality rate of 30-39 in South Korea is much higher than in France. As such, the optimal policy will suggest lowering the vaccination cutoffs for high-risk occupations and, to satisfy the vaccine budget constraint, mandate stay-at-home to a larger number of the elderly population.

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j provided by Salje et al. (2020), we obtain the infection rate for each U.K. minor occupation per $100,000$ people as

$$r_i = \frac{D_i}{\sum_j q_j d_j}, \tag{1}$$

where $q_j \in [0,1]$ denotes the fraction of age-group j according to the E.U. standard population distribution. Our maintained assumption is that exposure to the virus depends on occupation, but the infection fatality rate depends on patients' ages.

Next, we impute infection rates for the U.S. occupations. The approach we take exploits the relationship between an occupation's death rate and the degree of physical proximity that it involves. In an occupation with a higher physical proximity score, workers have to interact more closely with other people, such as co-workers or clients. Thus, presumably, the virus transmission rate is higher in occupations that require a higher degree of physical proximity, and, consequently, this will be reflected in death rates. Even as various social distancing measures are observed, we expect that occupations with a higher degree of physical proximity will still entail a higher infection risk than ones with a lower degree of physical proximity.

We estimate a fractional probit model (Papke and Wooldridge, 1996) using the infection rates, r_i, corresponding to each U.K. minor occupation we have derived based on (1) and physical proximity measures that are also provided by ONS. A worker employed in occupation i with degree of physical proximity $x_i \in [0,100]$ is going to be infected over two months with probability

$$P[\text{Infection}|x_i] = \frac{r_i}{100,000} = \Phi(\alpha + \beta x_i),$$

where Φ is the cumulative distribution function of the standard normal distribution. The estimates we obtain are $\hat{\alpha} = -2.672885$ (CI [-3.01342, -2.332349]) and $\hat{\beta} = 0.0091686$ (CI [0.0035577, 0.0147796]).

We then impute the infection rate for each US occupation based on these estimates.[3] In particular, we construct the infection rate per $100,000$ people over a two-month period for each U.S. occupation i with proximity score $x_i \in [0,100]$ as

$$\hat{r}_i = 100,000 * \Phi(\hat{\alpha} + \hat{\beta} x_i).$$

[3] One may consider bypassing the infection rate by matching the U.K. death rates by occupation to U.S. occupations. We do not take such approach as we need to find unconditional death rate for each occupation *and* age-group.

We use the proximity score developed by Mongey, Pilossoph, and Weinberg (2020) who calculate an the employment-weighted average of survey-based job characteristics for each 4-digit OCC occupation code based on O*NET data.

We also provide robustness in which we estimate the model using only mortality rates for occupations deemed to be essential in the U.K. to preempt a potential downward bias in the death rates that the stay-at-home order could have introduced. In this case, the parameter estimates from the fractional probit regression are $\hat{\alpha} = -2.392303$ and $\hat{\beta} = 0.005559$. The lower estimate of $\hat{\beta}$ implies that our estimates of the infection rates for U.S. occupations will be less responsive to proximity scores, i.e., more homogeneous infection rates across occupations. Hence, our main finding – vaccines to be distributed mostly by ages rather than occupations – becomes even stronger (Fig. S.5).

3 Results

We undertake three exercises. First, we find the optimal vaccine distribution under the assumption that there is no stay-at-home order, and everyone returns to work regardless of whether they have received a vaccine or not. Second, we derive the optimal vaccine distribution when a targeted stay-at-home order is implemented and that the individuals who are unable to return to work produce no output. That is, everyone who cannot return to work receives no wage for the stay-at-home order duration. Third, we derive the optimal vaccine distribution when a targeted stay-at-home order is implemented, but for some occupations, employees can work from home. In this case, individuals that can work from home receive the same wages as if they were to return to work, while individuals that cannot work from home produce no output and receive no wages for the duration of the stay-at-home order. For the last two exercises, 121 occupations deemed to be essential are exempt from the stay-at-home order. We assume that the length of the stay-at-home order is 2 months (Abbasi, 2020) to reflect the expected time lag until a vaccine becomes widely available and scale the yearly wage loss accordingly. We also cautiously assume that the initial supply of the vaccine allocated to employed people above the age of 16 is 60mil doses, covering approximately one-third of the employed workforce. Similarly, we assume that the vaccine effectiveness is 50% (Food and Drug Administration, 2020). We initially derive the optimal vaccination and stay-at-home policy when the constraint on the fraction of coronavirus fatalities is lax.

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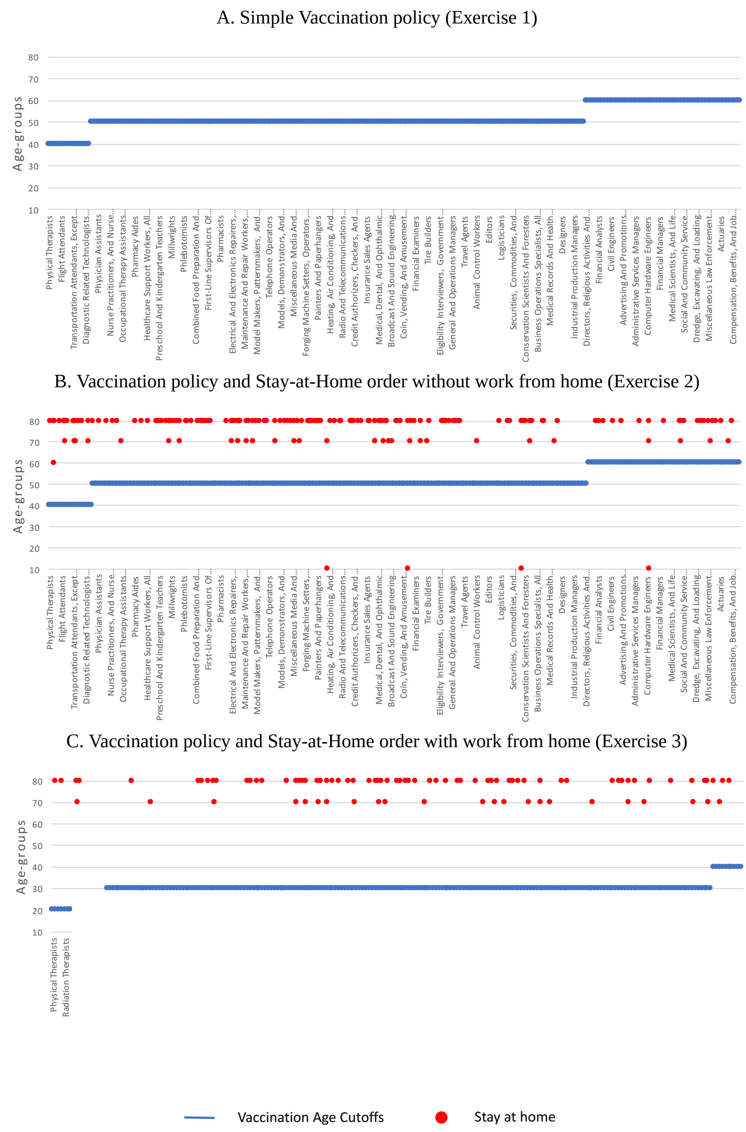

Figure 1: Age cutoffs for vaccinations and age groups staying at home. Occupations on the x-axis are ordered based on their infection risk. (A) The optimal vaccination policy showing the youngest age for each occupation that is eligible to receive the vaccine. (B) The optimal vaccination policy showing the youngest age for each occupation that is eligible to receive the vaccine, together with the occupation-age groups that are mandated to stay at home. (C) The optimal vaccination policy showing the youngest age for each occupation which cannot be done from home that is eligible to receive the vaccine, together with the occupation-age groups that are mandated to stay at home. Occupations that can be done from home do not receive a vaccine.

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The overall vaccine policy is presented in Fig. 1. We order occupations based on their infection risk, and show how the vaccine distribution policy and stay-at-home mandate depend on occupations and ages. The main insight from all three exercises is that age is more important than an occupation's infection risk when allocating vaccines optimally. The largest volume of vaccines are allocated to the populations of age 50-59, followed by age 60-69 in exercise 1 and 2, or age 30-39 in exercise 3 (Table S.2). The loss in economic benefits from being out of work plays a role in allocating vaccines only when a stay-at-home order is also used as a policy tool (as in exercise 2 and 3).

When we derive the optimal vaccine allocation absent of a stay-at-home order, all employed people above age 60 receive the vaccine (Fig. 1A). Some occupations, such as paramedics and flight attendants, are eligible to receive the vaccine if they are at least 40 years old. For many other occupations, including most other healthcare workers, the eligibility threshold for receiving the vaccine is age 50. There is naturally a trade-off between the infection risk associated with occupation and the risk of death related to age. For instance, any food processing workers above age 50 receive a vaccine, while financial advisors only receive the vaccine if they are above 60 years old.

When a stay-at-home order complements the vaccination policy, most employees who are at least 80 years old, and some in their 70s are mandated to stay at home (Fig. 1B). For the 80+ age-group, the risk of death is so substantial that a 50% effective vaccine is insufficient to overcome the loss in wages for the duration of the stay-at-home order. For a few occupations such as textile-related, the stay-at-home order targets teenagers as well. While the infection fatality rate for their age group is meager, the economic value of practicing their occupation given the corresponding infection rate does not justify the risk. In turn, the stay-at-home order allows nurses as young as 40 years old to receive vaccines.

Once we take into account that for some occupations, employees can work from home without any loss in wages, then the supply of the vaccine can be distributed only towards those occupations in which employees need to be present at their workplace. Allocating vaccines across fewer occupations implies that younger people, for instance, as young as 20 for nurses and food preparation workers, are now eligible to receive the vaccine (Fig. 1C).

We illustrate how priorities are assigned across different age groups for some selected occupations in Fig. 2. The top priority groups are shaded in the darkest blue and the groups with the next

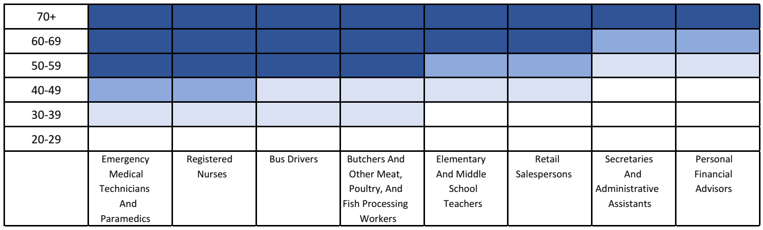

Figure 2: Priorities among some selected age-occupation groups. The groups with the top priority are marked in the darkest blue, and they receive vaccines even when the supply is 30 million doses. Lighter blues mark the groups that have the second and the third priority, and they will get vaccines when the supply is, respectively, 60 million and 100 million doses. The rest groups with the lowest priorities are marked in white.

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priorities in lighter blues. The top priority groups consist of high-risk populations in high-exposure occupations, consistent with an emerging consensus. They receive vaccines even under a very limited supply (30 million doses). The following priority groups receive when the supply increases to 60 million doses or 100 million doses. Young healthcare workers such as paramedics and nurses at age $30+$ (or $40+$) have about the same priorities as financial advisors at age 50+ (or, respectively, 60+). A scarcer supply of the vaccine (30 million doses) emphasizes occupational risk, with nurses, for instance, still being prioritized at age 50, while retail salespersons are eligible only at age 60.

Designating occupations as essential affect the optimal allocation of the vaccine only when a targeted stay-at-home order is also used (Fig. S.1). In designating, for instance, food processing workers as essential, we ensure that the individuals over 50 years old in this occupation receive vaccines. Otherwise, if food processing workers can be subject to the stay-at-home order, only the population under 70 years old, representing 99.3% of the workforce, can return to their workplace, with individuals over 50 years old (in exercise 2) or over 20 years old (in exercise 3) receiving the vaccine.

A more abundant initial supply of the vaccine also decreases the age of the youngest eligible recipients, as expected (Fig. S.4). Perhaps surprisingly, an infection fatality rate steeper with age, as presumably observed in South Korea, also decreases the youngest vaccine recipients' age. In this case, the risk of infection associated with an occupation becomes increasingly crucial in allocating vaccines. Thus, individuals employed occupations in which infections are likelier would receive the vaccine if they are at least 30 years old. The threshold age above which individuals become eligible to receive the vaccine is overall steeper (Fig. S.6). The stay-at-home order reinforces this effect because most people over 80 and many people in their 70s are not allowed to return to their workplaces.

Finally, our model allows us to derive the proportion of people that will still be infected with the virus even under the optimal vaccination policy, given any effectiveness and supply of the vaccine. When the vaccine is 50% effective, 1.37% of the employed workforce will still get the virus over the two months until the vaccine becomes widely available. When some occupations can be done at home, the proportion decreases to 0.53%. An increase in the vaccine effectiveness to 70% changes the vaccine allocation (Fig. S.2) and reduces the fraction of infected people close to 1.27% (exercise 1 and 2) or to 0.41% (exercise 3). However, the fraction of infected people decreases also as the supply of the vaccine increases. With 100mil doses, the fraction of infected people decreases to 1.18% (in both exercises 1 and 2) even with vaccine effectiveness of 50%.

One may find that even the optimal vaccination policy would surrender to too many infections and potentially too many fatalities. In exercise 1, the vaccine effectiveness should be at least 55.06% for the (unconditional) mortality rate associate with SARS-CoV-2 to be comparable with the mortality rate during the average flu season.[4] If the effectiveness is at most 50%, such low fatalities are feasible only with a more stringent stay-at-home order targeting elderly individuals (exercises 2 and 3). In these cases, vaccines will be re-allocation from the youngest populations in high-risk occupations toward older people in lower risk occupations (Fig. S.7, relative to Fig. 1B).

In deriving the optimal allocation of vaccines based on age and occupations, we implicitly considered that people are exposed to the coronavirus only through their occupations. Naturally, spending time with family, shopping, or engaging in leisurely activities are other activities through which infection with the virus can occur. If people face the same non-occupation related infection risk, our analysis suggests that the optimal allocation of vaccines would be tilted even more towards the elderly. In other words, exposure to infection risk outside working hours dampens the role of the infection risk within working hours in the allocation of vaccines.

A model in which the population faces a death risk that depends on age and an infection risk that depends on occupation allows us to determine the optimal vaccine distribution policy for all U.S. employed population above the age of 16. Identifying priority groups for COVID-19 vaccination is

[4]CDC reports that seasonal flu has resulted in between 12,000 - 61,000 deaths annually since 2010. We take the average 38,000 and divide it by 6 to account for a two-month period in our setup. The resulting number of flu-related deaths represents about 0.012% of about 320 million U.S. population.

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critical for implementation planning, and our analysis can be input into how to allocate the vaccine across different populations.

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S Supplementary Text

S.1 Physical Proximity Scores

O*NET asks a number of questions about individuals' working conditions and day-to-day tasks of their job. To evaluate proximity, the question asks, "How physically close to other people are you when you perform your current job?". Respondents provide a response on a scale between one and five, one indicating that the respondent does not work near other people (beyond 100ft.), while five indicating that they are very close to others (near touching). More information on these questions is provided in the Instructions for Work Context Questionnaire (Q 21), published by O*NET.

The responses to this question are standardized by Mongey, Pilossoph, and Weinberg (2020)to a scale ranging from 0 to 100 as follows. First, O*NET reports the answers to the survey using the fine occupation SOC-code. Mongey, Pilossoph, and Weinberg (2020) calculate an employment-weighted average, $\bar{m}_i$, of the response to this question that corresponds to each occupation, i, classified according to the 4-digit Census OCC code. Second, Mongey, Pilossoph, and Weinberg (2020) follow the procedure used by O*NET and re-scale the survey answer to the interval $[0, 100]$ using the following equation:

$$x_i = \frac{(\bar{m}_i - \bar{m}_i^{\min})}{(\bar{m}_i^{\max} - \bar{m}_i^{\min})} * 100,$$

where x_i is the final physical proximity standardized score for occupation i.

S.2 Work-from-Home Occupations

The work-from-home classification of occupations has been developed by Mongey, Pilossoph, and Weinberg (2020) and Dingel and Neiman (2020) using O*NET survey answers from the Work Activities Questionnaire and Work Context Questionnaire. The Work Context Questionnaire includes questions aiming to capture the "physical and social factors that influence the nature of work" such as interpersonal relationships, physical work conditions, and structural job characteristics. The Work Activities Questionnaire includes questions aiming to capture the "general types of job behaviors occurring on multiple jobs" such as the input of information, mental processes, and work output.

We use the classification of Mongey, Pilossoph, and Weinberg (2020) because they provide an

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employment weighted aggregation at the 4-digit Census OCC codes. In particular, they aggregate 18 occupational attributes based on answers to the questions Q4, Q14, Q17, Q18, Q29, Q33, Q37, Q43, Q44, in the Work Context Questionnaire, and Q4A, Q16A, Q17A, Q18A, Q20A, Q22A, Q23A, Q32A in The Work Activities Questionnaire. The responses to these questions are standardized to a work-from-home score ranging from 0 to 1 following the same procedure as the one used to calculate the physical proximity score. In the next step, an occupation is classified either as that it can be done from home if its work-from-home score is above the median, or that it cannot be done from home if its work-from-home score is below the median.

We use this classification to derive the optimal allocation of vaccines when a stay-at-home order is used, and some occupations can be done from home (exercise 3). However, we acknowledge that this classification has limitations, as some occupation categories may be too coarse. For instance, physicians and surgeons have been classified as a work-from-home occupation. While for many physicians telemedicine seems feasible for limited periods of time, as has been evident during the lockdown in the U.S., we understand that telemedicine is not applicable for surgeons or critical care doctors. Another example is teachers, who are also classified as a work-from-home occupation. At the same time, our approach is flexible, and an optimal vaccine allocation can be derived under various specifications, including fractional ones, for which occupations are done from home. Thus, as some physicians return to hospitals, and some teachers return to teach in person, these occupations can be re-classified partly as occupations that are not done from home, and our model will assign vaccines accordingly.

S.3 Essential Occupations

We have designated occupations to be essential based on the guidelines issued by the Cybersecurity and Infrastructure Security Agency (CISA). Our classification is inherently subjective and is also subject to the limitation that some occupations are very coarse. For instance, we have classified network and computer systems administrators as an essential occupation according to the guidelines issued by CISA. However, we acknowledge that it is likely that not all system administrators are essential workers. It is re-assuring that designating an occupation as essential plays no role when a simple vaccination policy is considered, as in exercise 1.

Table S.1: Vaccine Distribution by Ages.

	20-29	30-39	40-49	50-59	60-69	70-79	80+
Exercise 1	0	0	1,503,581	27,180,360	24,040,335	6,094,810	1,180,914
Exercise 2	0	0	1,757,797	27,216,478	24,039,593	6,030,180	955,952
Exercise 3	1,571,230	16,111,831	15,109,864	15,223,264	9,520,810	2,123,659	339,342

Table S.2: The Infection Fatality Rate by age-groups reported in South Korea.

Age group	Infection fatality rate (%)
< 19	0
20-29	0
30-39	0.13
40-49	0.17
50-59	0.63
60-69	2.35
70-79	9.33
80+	25.26

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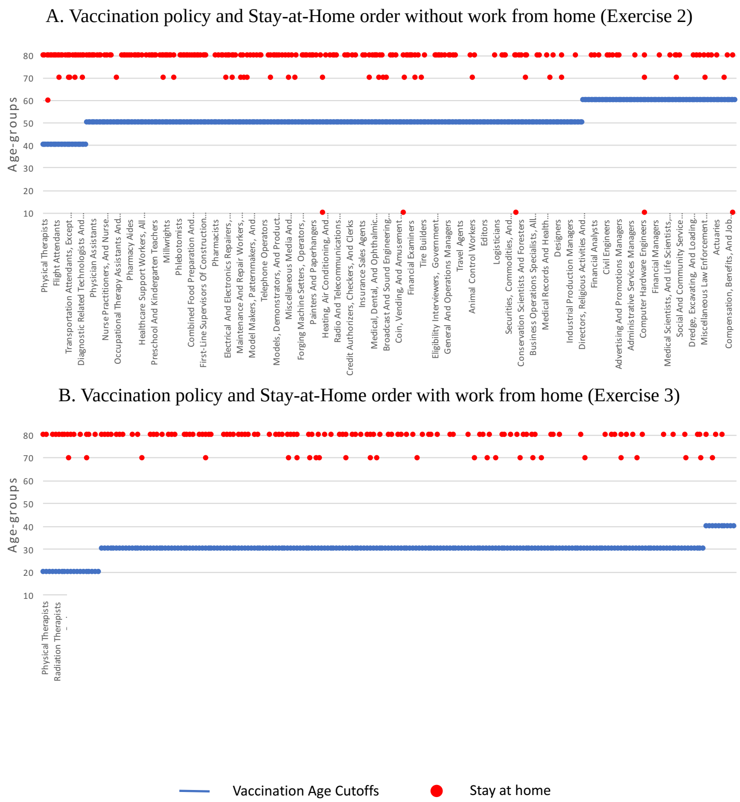

Figure S.1: Age cutoffs for vaccinations and age groups staying at home when no occupations are designated to be essential. Occupations on the x-axis are ordered based on their infection risk. (A) The optimal vaccination policy showing the youngest age for each occupation that is eligible to receive the vaccine, together with the occupation-age groups that are mandated to stay at home. (B) The optimal vaccination policy showing the youngest age for each occupation, which cannot be done from home that is eligible to receive the vaccine, together with the occupation-age groups that are mandated to stay at home. Occupations that can be done from home do not receive a vaccine.

Note: We omit exercise 1, which remains the same as in Fig. 1A. Exercise 1 requires workers of all occupations to return to work regardless of being vaccinated or not. Designating an occupation to be essential does not affect the optimal vaccine allocation in this case.

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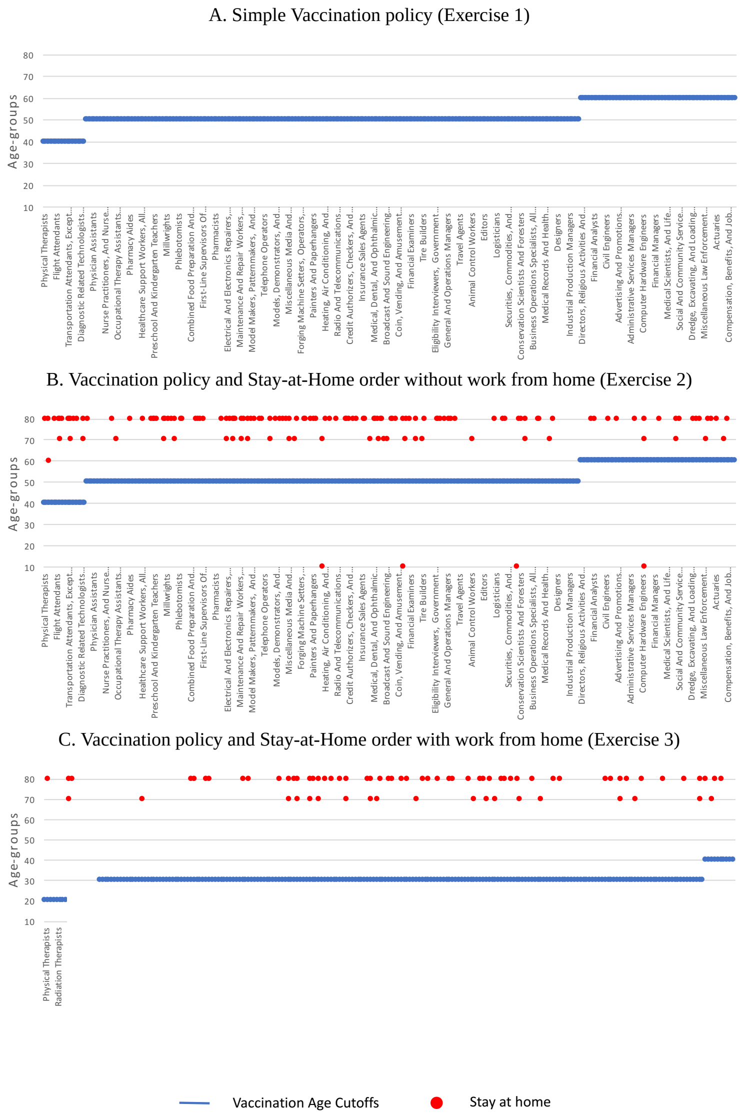

Figure S.2: Age cutoffs for vaccinations and age groups staying at home when vaccine effectiveness is 0.7. Occupations on the x-axis are ordered based on their infection risk. (A) The optimal vaccination policy showing the youngest age for each occupation that is eligible to receive the vaccine. (B) The optimal vaccination policy showing the youngest age for each occupation that is eligible to receive the vaccine, together with the occupation-age groups that are mandated to stay at home. (C) The optimal vaccination policy showing the youngest age for each occupation which cannot be done from home that is eligible to receive the vaccine, together with the occupation-age groups that are mandated to stay at home. Occupations that can be done from home do not receive a vaccine.

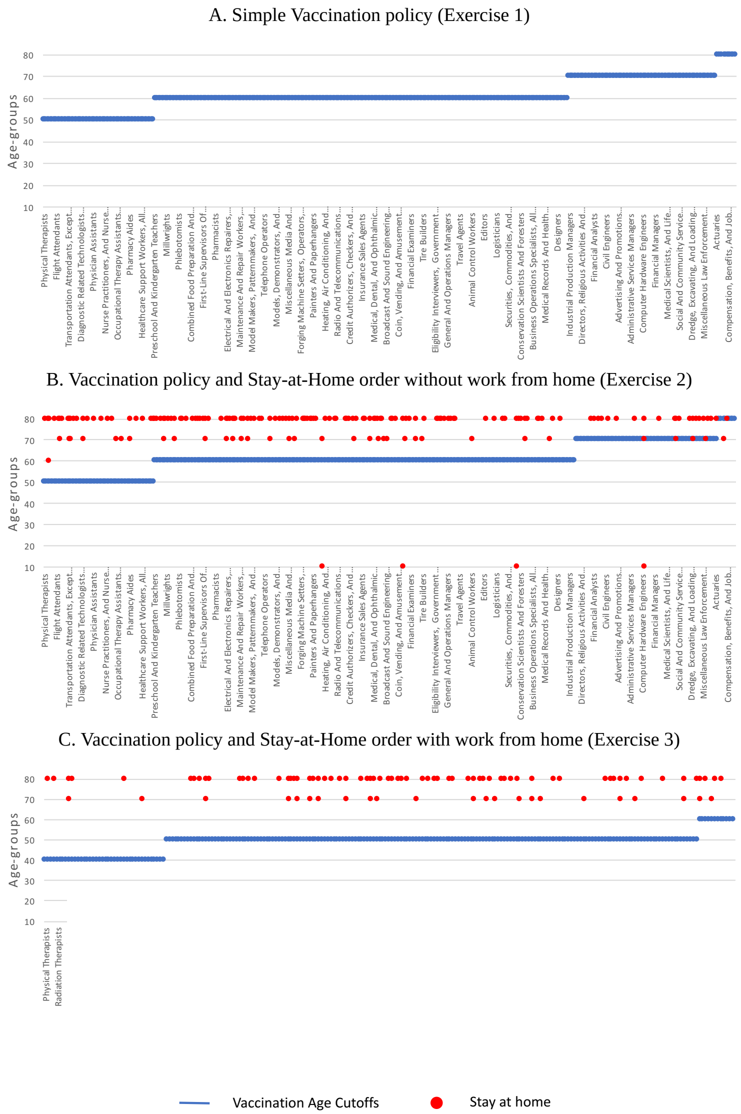

Figure S.3: Age cutoffs for vaccinations and age groups staying at home, when the supply of vaccines is 30mil doses. Occupations on the x-axis are ordered based on their infection risk. (A) The optimal vaccination policy showing the youngest age for each occupation that is eligible to receive the vaccine. (B) The optimal vaccination policy showing the youngest age for each occupation that is eligible to receive the vaccine, together with the occupation-age groups that are mandated to stay at home. (C) The optimal vaccination policy showing the youngest age for each occupation which cannot be done from home that is eligible to receive the vaccine, together with the occupation-age groups that are mandated to stay at home. Occupations that can be done from home do not receive a vaccine.

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Figure S.4: Age cutoffs for vaccinations and age groups staying at home, when the supply of vaccines is 100mil doses. Occupations on the x-axis are ordered based on their infection risk. (A) The optimal vaccination policy showing the youngest age for each occupation that is eligible to receive the vaccine. (B) The optimal vaccination policy showing the youngest age for each occupation that is eligible to receive the vaccine, together with the occupation-age groups that are mandated to stay at home. (C) The optimal vaccination policy showing the youngest age for each occupation which cannot be done from home that is eligible to receive the vaccine, together with the occupation-age groups that are mandated to stay at home. Occupations that can be done from home do not receive a vaccine.

Note: While, in exercise 3, the vaccination cutoffs may appear to be non-monotonic in occupations' risks, that is only because some occupations have no teenage workers.

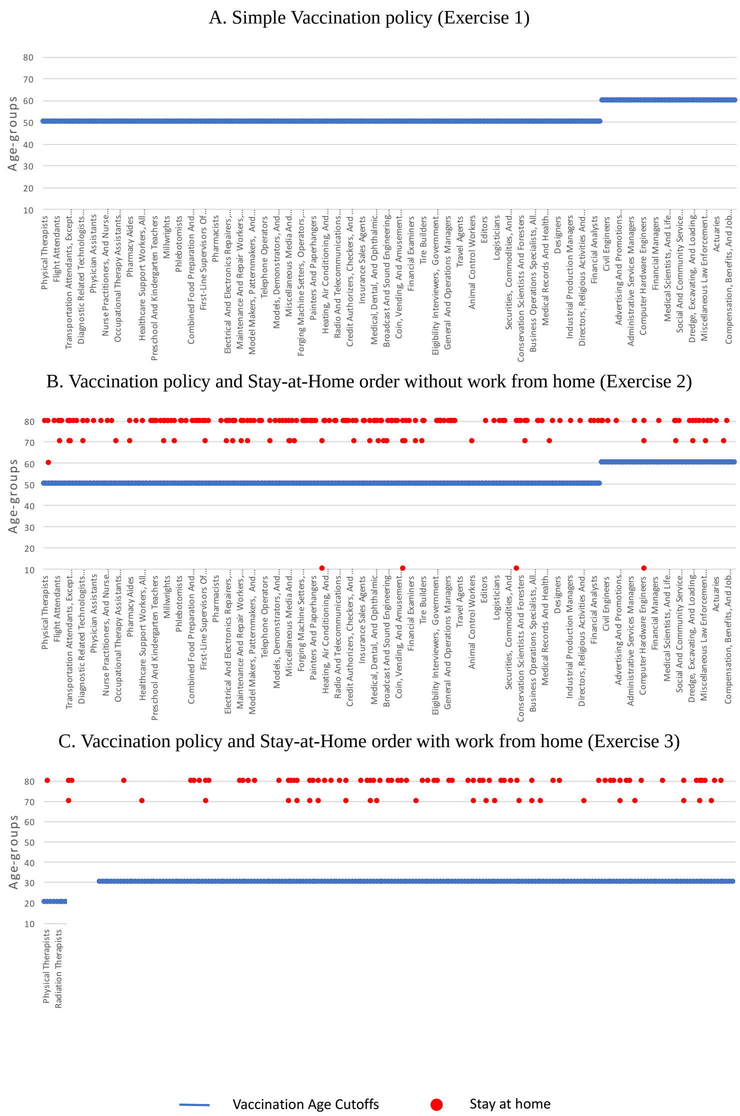

Figure S.5: Age cutoffs for vaccinations and age groups staying at home (probit estimation with only essential U.K. occupations, α=-2.392303 and β=0.005559). Occupations on the x-axis are ordered based on their infection risk. (A) The optimal vaccination policy showing the youngest age for each occupation that is eligible to receive the vaccine. (B) The optimal vaccination policy showing the youngest age for each occupation that is eligible to receive the vaccine, together with the occupation-age groups that are mandated to stay at home. (C) The optimal vaccination policy showing the youngest age for each occupation which cannot be done from home that is eligible to receive the vaccine, together with the occupation-age groups that are mandated to stay at home. Occupations that can be done from home do not receive a vaccine.

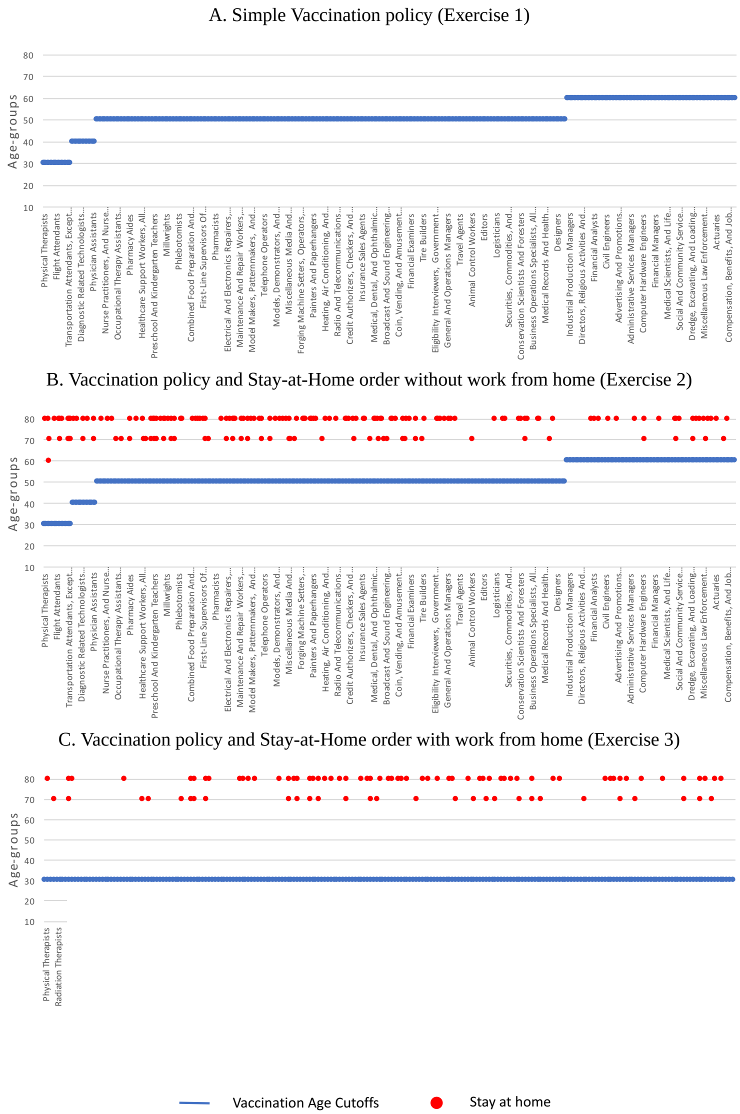

Figure S.6: Age cutoffs for vaccinations and age groups staying at home based on South-Korean infection fatality rates from Table S3. Occupations on the x-axis are ordered based on their infection risk. (A) The optimal vaccination policy showing the youngest age for each occupation that is eligible to receive the vaccine. (B) The optimal vaccination policy showing the youngest age for each occupation that is eligible to receive the vaccine, together with the occupation-age groups that are mandated to stay at home. (C) The optimal vaccination policy showing the youngest age for each occupation which cannot be done from home that is eligible to receive the vaccine, together with the occupation-age groups that are mandated to stay at home. Occupations that can be done from home do not receive a vaccine.

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A. Vaccination policy and Stay-at-Home order without work from home (Exercise 2)

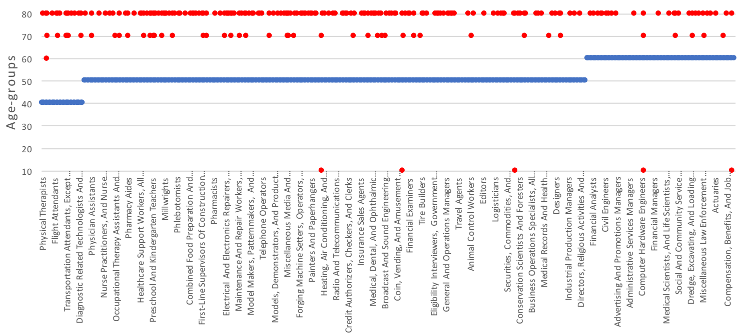

Figure S.7: Age cutoffs for vaccinations and age groups staying at home so that coronavirus-related mortality rate is comparable to the regular flu mortlaity rate. Occupations on the x-axis are ordered based on their infection risk. (A) The optimal vaccination policy showing the youngest age for each occupation that is eligible to receive the vaccine, together with the occupation-age groups that are mandated to stay at home. The mortality rate constraint is binding in exercise 2 but not in exercise 3.

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Wind of Change? Experimental Survey Evidence on the COVID-19 Shock and Socio-Political Attitudes in Europe[1]

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Covid Economics 44, 25 August 2020: 72-153

This paper investigates whether the COVID-19 crisis has affected the way we think about (political) institutions, as well as our broader (policy) attitudes and values. We fielded large online survey experiments in Italy, Spain, Germany and the Netherlands, well into the first wave of the epidemic (May-June), and included outcome questions on trust, voting intentions, policies & taxation, and identity & values. With a randomised survey flow we vary whether respondents are given COVID-19 priming questions first, before answering the outcome questions. With this treatment design we can also disentangle the health and economic effects of the crisis, as well as a potential "rally around the flag" component. We find that the crisis has brought about severe drops in interpersonal and institutional trust, as well as lower support for the EU and social welfare spending financed by taxes. This is largely due to economic insecurity, but also because of health concerns. A rallying effect around (scientific) expertise combined with populist policies losing ground forms the other side of this coin, and suggests a rising demand for competent leadership.

1 We are extremely grateful to Simona Cicognani, Gloria Di Caprera, Gemma Dipoppa, Marco Le Moglie, Till Stowasser, Amedeo Piolatto and Laura Villalobos for excellent feedback and comments. Excellent research assistance was provided by Magnus Haselier. We gratefully acknowledge generous financial support from the Max Planck Society.

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Wind of Change?

Experimental Survey Evidence on the COVID-19 Shock and Socio-Political Attitudes in Europe

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Abstract

This paper investigates whether the COVID-19 crisis has affected the way we think about (political) institutions, as well as our broader (policy) attitudes and values. We fielded large online survey experiments in Italy, Spain, Germany and the Netherlands, well into the first wave of the epidemic (May-June), and included outcome questions on trust, voting intentions, policies & taxation, and identity & values. With a randomised survey flow we vary whether respondents are given COVID-19 priming questions first, before answering the outcome questions. With this treatment design we can also disentangle the health and economic effects of the crisis, as well as a potential "rally around the flag" component. We find that the crisis has brought about severe drops in interpersonal and institutional trust, as well as lower support for the EU and social welfare spending financed by taxes. This is largely due to economic insecurity, but also because of health concerns. A rallying effect around (scientific) expertise combined with populist policies losing ground forms the other side of this coin, and suggests a rising demand for competent leadership.

JEL classification Codes: D72, H51, H53, H55, O52, P52
Keywords: COVID-19, Social Trust, Institutional Trust, Survey Experiment, European Union, Welfare, Health, Taxation, Accountability, Populism, Values

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1 Introduction

The COVID-19 crisis is a perfect storm, unprecedented in peacetime. It inextricably blends elements of what was first a health emergency, and quickly evolved into a full-blown economic and social crisis. Hundreds of thousands have seen their health directly put in jeopardy, with many more indirectly worried about future waves of infection. Government measures to control the exponential spread of the virus have ripped through our economies, and brought about what is already called the 'great interruption'.[1] The resulting job losses and economic insecurity will likely be of the same scale as the economic and social-distancing measures themselves, and will change consumption patterns and working life for good. The crisis is also global, has to different degrees spared no one, and has as such widened existing gaps of inequality or social injustice as well.

Because of each of these reasons, and especially as they are at play simultaneously, the crisis can be expected to profoundly change the way individuals interact, but also relate to their institutional background. Both are vital steppingstones to understanding how any society, and its politics, function.

In this paper we investigate whether a crisis on the scale of the COVID-19 crisis can indeed bring about a critical juncture, affecting not just the way we vote and think about politics, but also our attitudes and underlying value systems. To this end we have fielded several online survey experiments in Italy, Spain, Germany and the Netherlands, well into the first wave of the epidemic (May-June). Casting a sufficiently wide net to capture the most relevant trends that could be affected by the crisis, we include four blocks of outcome questions relating to (institutional) trust, voting intentions, policies & taxation, and identity & values. We find significant treatment effects in all four categories, indicating that the crisis has brought about severe drops in interpersonal and institutional trust, as well as lower support for the EU and social welfare spending financed by taxes. Maintained support for incumbents and experts combined with populist policies losing ground turns out to be the other side of this coin, and hints at a rising demand for competence.

The choice of our four outcome categories – trust, voting intentions, policies & taxation, and identity & values – is deliberate. To gauge whether the COVID-19 crisis

[1] The latest GDP figures for the second quarter of 2020, for example, stand at a dismal -18.5% for Spain, -20.4% for the UK, -12.4% for Italy, -13.8% for France, -10.1% for Germany, -11.9% for the EU as a whole and -9.5% for the US (all compared to the previous quarter).

resulted in a critical juncture, a logical starting point is to look for shocks in either direction in *existing* trends. Our first category relates to the trend that trust in political institutions has been eroding for decades, whilst interpersonal trust has not always followed suit. Our second dimension, 'voting intentions', taps into the trend that over the last decade voters have shied away from centrist political platforms, increasingly voting for more extreme parties promising to tackle the sources of rising cultural and economic insecurity. Experts, the media and established policy institutions have often been discredited in the process, which has eroded institutional trust as well. Depending on the context, moreover, such anti-establishment platforms have successfully taken aim at austerity and globalisation, and favoured tax rises or an expansion of redistributive safety nets. Values or identities have also been recast along a more nationalist locus, with international organisations such as the EU effectively used as scapegoats. Both these trends are captured by our third and fourth outcome categories: 'policies & taxation' and 'identity & values'.

Our results suggest a reversal of some of these trends, and a reinforcement of others. We adopt a randomised survey flow design in which the order of the questions presented to the respondents is controlled, and designed so as to focus their attention on the epidemic (or not). Specifically, our treatment groups answer a set of COVID-19 -related questions first, thus activating crisis-awareness, after which they have to answer the full set of outcome questions. The control groups receive the two blocks of questions in reversed order instead: the outcome questions first and the COVID-19 priming questions after. This way, the control group's answers to the outcome questions cannot be influenced by the COVID-19 focus of the priming questions. We are thus able to identify the extent to which socio-political attitudes are affected by putting the crisis front and center in respondents' minds.

Moreover, to disentangle the impact of the different sides to the crisis, we have subdivided our COVID-19 priming questions along three dimensions. First, a health dimension, covering all health and social aspects of the crisis, with questions on social distancing, testing, contact with the virus, etc. Second, an economic dimension, eliciting economic concerns with questions on possible job loss, future opportunities, etc. Lastly, a 'conflict' dimension, asking whether respondents perceive the crisis as a conflict against an invisible enemy, and whether they see unity and national solidarity as the main 'winning' strategies. This then allows us to construct three conditions: a

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first condition consisting of questions related to the health dimension *only* (the health condition), a second related to the health *and* economic dimension (the economic condition), and a third related to the health *and* conflict dimension (conflict condition). Each of these conditions is presented to a third of the overall treatment group, which gives us three sub-treatment groups. This way, we can effectively pinpoint the effect of the economic- and conflict-related dimensions of the crisis, by comparing the response of the economic/conflict condition to that of the health condition.[2]

Pooling all treatments, first of all, our general results are the following. Social trust drops considerably for respondents in the treatment group, as does trust in politicians, the media and the EU. Wider EU-related attitudes on the perceived benefits and efficacy of the EU, as well as a sense of attachment to Europe, also fall. This is confirmed by our behavioural outcome measure – i.e. the willingness to read and advise on the use of a pro-EU speech for educational purposes – which is also significantly lower after answering COVID-19 questions. Trust in the police, experts and scientists goes up on the other hand, whilst trust in the government remains more or less stable.

On the policy side, we find that the support for financing the welfare state with taxes is negatively affected. This holds across all surveyed expenditure categories – poverty alleviation, health expenditure, unemployment benefits and pensions – and coincides with a higher reported dissatisfaction with the general tax burden. We furthermore find evidence that 'populist' attitudes have weakened, both in terms of support for a strong leader to deal with a crisis, and the preference to let the 'people' make the most important policy decisions instead of politicians. However, we do not find any effect on voting intentions, both for mainstream and populist parties.

Our results with respect to political institutions can be explained by two countervailing mechanisms: what we will call a 'disillusion' effect on the one hand, and a 'rally around the flag' effect on the other. The former derives from the stylized fact that crises of all kinds, from natural disasters to economic shocks, will always overwhelm governing institutions to some degree. By definition a crisis is unexpected, and citizens may have had higher expectations of their governments and institutions to grapple with the uncertainty, to be prepared for the shock, and manage it properly once it occurs.

[2]Explicitly activating the health dimension in all three conditions thus allows us to take the health component as fixed and to cleanly identify the additional impact of the other two dimensions being activated. This is necessary, since the health dimension by itself may already (partially) trigger economic or conflict related elements of the crisis.

Disappointment and disillusion are therefore unavoidable to some extent, which then undermines trust. The COVID-19 crisis certainly ticks all of these boxes and more, as a highly infectious viral outbreak runs an exponential course and is hence even more unpredictable.

The second, 'rally around the flag' mechanism is also well-known and works in the opposite direction. Precisely because a crisis represents a situation which is out of the ordinary, citizens are more easily united around a common cause, putting their shoulders under any kind of crisis response with enthusiasm, and even patriotism if the threat concerns one's own country. Again the COVID-19 crisis fits perfectly here, as the pandemic was mostly framed as a national struggle, rather than a global one.

The 'disillusion' effect could then explain why we find decreasing trust in politicians and the EU, as these are seen to have failed to anticipate the crisis and manage it well. Similarly, the 'disillusion' might also concern fellow-citizens, if these are seen as COVID-19 (super)spreaders. Both mechanisms can then translate into the decreased willingness to pay into the redistributive system, as the political class, running these programs, and the people, benefiting from them, are trusted less, as also found in Daniele and Geys (2015). On the other hand, and because national governments and especially experts were seen to actively (try to) take on the brunt of the crisis, trust in those 'in charge' received a boost, with the 'rally around the flag' effect as a strengthening factor.

Of course, to better found both mechanisms we need to dig deeper. The design of our survey experiment, set up to disentangle the impact of each of the different sides to the COVID-19 crisis, offers a first avenue here. Compared to the general analysis where all respondents were pooled, important differences emerge when focusing strictly on the health condition in our first sub-treatment. Trust in politicians levels off less, trust in the government turns slightly positive and most importantly, voting intentions swing in favour of the incumbent national government. Disagreement with individual and general tax burdens also remains neutral. Both outcomes suggest the 'disillusion' effect shines through less if only social and health aspects of the crisis are activated, and that 'rally around the flag' dynamics work in favour of the incumbent government but less so for politics as a whole, let alone EU institutions.

This picture changes drastically, however, once we include the economic dimension. This second sub-treatment shifts all trust indicators squarely into negative territory, and activates disagreement with the tax burden. It also marks a lower willingness to give

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up personal freedom in exchange of individual and public safety, and (further) erodes support for populist as well as incumbent parties. These results indicate the 'disillusion' effect is in full swing when the economic consequences of the crisis are brought to mind. Inversely, when respondents are presented with the health and 'conflict' dimensions in the third sub-treatment, support for science and experts shoots up significantly, leaving all other indicators constant. This again suggests a 'rally around the flag' effect is at play, here centred on (scientific) expertise.

Another way to underpin our proposed mechanisms is to use our treatment questions for further heterogeneity analysis. What we find is that treated respondents who willingly followed the emergency measures report higher levels of trust in institutions, and perceive their individual and the general tax burden as less problematic. This can be interpreted as a proxy of the 'rally around the flag' effect, in the form of cooperation with the government. Among those who are concerned about their health, a similar argument can be made, which shows in slightly higher levels of institutional trust but mostly in support for taxation and welfare programs.

Of course, our results should first and foremost be interpreted as a shock, diverging from existing trends. Whether we have in fact uncovered a critical juncture setting these trends on an entirely different path, can only be ascertained by conducting follow-up waves of our survey experiment. Depending on how governments will manage the economic recovery and/or a possible resurgence of the virus will be a crucial factor here. In any case it will be interesting to see whether the rising demand for competent leaders and policies we uncover is met in the future, or whether the 'disillusion' effect will eventually be translated into increased populist support.

The paper is organized as follows. Sections 2 and 3 present the details of the survey and the experimental design. Sections 4 and 5 present the estimation strategy and our findings. We conclude in Section 6.

Related Literature

Our work first of all contributes to the small yet growing strand of papers looking into the effect of the COVID-19 crisis on trust and political attitudes. The main innovation of our paper is to study the overall effect of the crisis by providing experimental evidence on a comprehensive set of socio-political attitudes across several countries, as well as the mechanisms behind this effect. While previous studies with a similar scope are based on

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correlational evidence or focus on COVID-19 specific aspects (e.g. lockdown effects), so far experiments have been used only to study specific outcomes in a one-country context.

More specifically, the analysis in Brück et al. (2020) is based on a new global survey and uses correlational statistics. It shows that those who have had contact with sick people and are unemployed exhibit lower trust in people and institutions (police, courts, local & national government), whilst personally experiencing symptoms of the disease did not play a part. Using an online survey fielded in March 2020 in several Western European countries, Bol et al. (2020) compare respondents who took the survey before and after the start of the lockdown. Their results suggest lockdowns have increased voting intentions for incumbent parties, trust in government, and satisfaction with democracy. Bækgaard et al. (2020) arrive at similar conclusions based on a Danish survey. Relying on experimentally induced variation our treatment effects also suggest such a 'rallying effect' is at play, yet our economic treatment condition marks the extent to which it can be crowded out by the economic fallout of the crisis. This suggests the lockdown rally itself was temporary, and tapered out as more material and social consequences of the crisis manifested itself.

Combining the approach of Bol et al. (2020) and Brück et al. (2020), Amat et al. (2020) compare reported political attitudes in January and March for a panel of 818 respondents in Spain. Having an infected relative or friend is shown to boost the preference for technocratic government and competent management. They also find correlational evidence that the crisis has eroded political trust and democratic preferences, as well as increased support for authoritarian emergency measures and strong leadership, even at the cost of personal freedom. Whilst the trust and competence results are in line with our experimental treatment effects, we find the inverse when it comes to populist attitudes and the importance of civil liberties. This could be because the incompetence of populist rulers in other countries had been exposed by the time our study was fielded in May/june.[3]

Foremny et al. (2020) implement two information treatments on the COVID19 fatality rate – across age groups and incidence across regions – on a pool of 1000 respondents in Spain in early April. Results suggest that preferences for health care expenditures have almost doubled, especially in terms of ICU capacity and when respondents belong

[3]In terms of political fallout of the crisis, see also Merkley et al. (2020) on the effect on political and public cross-partisan consensus, and Grossman et al. (2020) as well as Kushner Gadarian et al. (2020) on the importance of partisan affiliation to maintain compliance with lockdown measures.

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to groups facing a higher risk. Our heterogeneity subconditions are in line with this finding, showing that those concerned about the virus or those that have contracted it, would like to spend more taxes to finance health care.

In a survey experiment conducted in the Czech Republic, Bartos et al. (2020) employ a similar experimental strategy to ours and find evidence that the pandemic has fuelled respondents' hostility towards foreigners, but not towards domestic out-groups and minorities. This aligns with our own finding that treated respondents feel health care should be reserved to 'own' citizens. Durante et al. (2020), lastly, find that in Italian areas where civic capital is higher, compliance was stronger. While they thus observe that more trustful individuals are more willing to comply with the rules, we find that these individuals are also more distrustful of others when primed with COVID-19 questions.

Second, our focus also overlaps with the literature studying the effect of pandemics on institutional trust and political preferences. Aksoy et al. (2020) find that epidemic exposure in what psychologists refer to as an individual's "impressionable years" (ages 18 to 25) has a persistent negative effect on confidence in political institutions and leaders. They find similar negative effects on confidence in public health systems, suggesting that this loss of confidence is associated with healthcare-related policies and their limitations at the time of the epidemic. Our findings chime well with these results, although we also uncover the sizeable effect of economic insecurity related to the crisis. Importantly, since the main premise of Aksoy et al. (2020) is that exposure to a pandemic during one's impressionable years leads to persistent effects on trust, this would indicate we have indeed uncovered a critical juncture. Blickle (2020) secondly, show that influenza mortality in 1918-1920 is correlated with societal changes, as measured by municipal spending and city-level extremist voting, in the subsequent decade.

The rally-around-the-flag literature, thirdly, holds that approval rates for incumbents usually increase when a crisis is due to an external conflict, while they decrease when it is due to an economic downturn.[4] The COVID-19 pandemic exhibits both of these characteristics. It can be perceived as an inevitable catastrophe, as an external enemy to fight against. But it can also be perceived as economic disaster (Fetzer et al., 2020), from which the government should have protected citizens. In line with this literature, we find that support for the incumbent is maintained or even increases in the health

[4]See, among others, Hetherington and Nelson (2003), Gibler et al. (2012) and Ariely (2017), and the literature therein.

sub-treatment, while it decreases in the economic sub-treatment.

Since the economic effects of the pandemic indeed seem to play a crucial role, fourthly, our work is close to the literature documenting dissatisfaction with the political establishment during severe economic crises. Stevenson and Wolfers (2011) document an enormous loss of trust in US political institutions in the aftermath of the Great Recession. Frieden (2016) observes increased dissatisfaction with EU institutions over the course of the 2008-2012 crisis (see also Dustmann et al. (2017), Hernández and Kriesi (2016); Guiso et al. (2020); Margalit (2019)). Algan et al. (2017) uncover a strong relationship between economic insecurity and populist voting in Europe. We do not find clear evidence that the COVID-19 crisis strengthens the preference for populist parties, the association even becomes clearly negative in the economic sub-treatment.[5]

The perceived mishandling of an economic crisis by the political class and a country's broader institutions then brings about a sense of disillusion, which in turn undermines trust. This mechanism can also work in different contexts, however. In that light our paper also relates to the literature studying whether natural disasters, and their fallout, help or hurt politicians' electoral fortunes. Some studies argue that voters punish incumbent politicians indiscriminately after such disasters (Achen and Bartels (2004, 2017)). Conversely, other studies find that voters are able to assign praise and blame by considering incumbent reaction to the natural disaster (Healy and Malhotra (2009); Bechtel and Hainmueller (2011); Gasper and Reeves (2011); Heersink et al. (2017)).

Lastly, our research also ties into the literature investigating the effect of crises on social trust. Work on the effect of global pandemics on social and interpersonal trust specifically, however, is rather sparse. Aassve et al. (2020) find evidence that the Spanish flu epidemic of 1918/19 had long lasting negative consequences for social trust. Using the fact that cultural traits and attitudes tend to be passed on across generations, they employ GSS (General Social Survey) data from respondents who are direct descendants of migrants to the US to construct an estimate of social trust before and after the pandemic for each country of origin. We expand on these findings by using experimental variation to show that there is a causal negative effect of the pandemic on social trust. From a wider perspective, Owens and Cook (2013) find that worsening local economic conditions due to the 'Great Recession' of 2008 had a negative effect on interpersonal

[5]As mentioned above, the populist economic recipe seems to have lost its specific appeal when it comes to COVID-19 , possibly because the incompetence of some populist leaders became apparent during the crisis.

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trust and Kevins (2019) detects a negative effect of labour market vulnerability on social trust. Meanwhile, Bauer et al. (2016) show that wars can strengthen interpersonal trust and cooperation.

For a further extensive overview of the rapidly expanding body of work on the economics of COVID-19 in general, we refer to Brodeur et al. (2020), and the literature therein.

2 The Survey

We hired the professional survey company Respondi to handle the distribution of the link to our online survey in four European countries: Germany, Italy, the Netherlands and Spain.[6] The survey was simultaneously distributed in all four countries in the first two weeks of June 2020. From each country, we collected data from a random sample of adults (below 70 years of age) exceeding 2000 individuals, achieving a total sample size of 8235 observations, as detailed in Table 1.[7] We aimed at representativeness of the samples by age, geographic area of residence and gender. We further tried to achieve a distribution of disposable equivalized household income as close as possible to the one provided by Eurostat.[8] The English survey questionnaire was translated in all languages by the native-speaking authors, except for the Spanish version which was instead translated by professional translation services offered by Respondi. Thus the survey was administered in each country's local language.[9]

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[6]https://www.respondi.com/EN/

[7]We are a priori able to detect a minimum effect MDE=0.12 on standardised outcome measures at $\alpha = 0.05$ and power $\pi = 0.8$ in within-country analyses.

[8]EU-SILC: https://ec.europa.eu/eurostat/web/main/home

[9]The English translation of the full questionnaire can be found in Appendix F. The interested reader can take the survey in the local languages by using the links below.
Dutch: `https://taxmpg.eu.qualtrics.com/jfe/form/SV_85Ocx8lc4806tzT`
German: `https://taxmpg.eu.qualtrics.com/jfe/form/SV_5ouJ8nUBnj11lMp`
Italian: `https://taxmpg.eu.qualtrics.com/jfe/form/SV_5apXa5HwDkB55it`
Spanish: `https://taxmpg.eu.qualtrics.com/jfe/form/SV_0ln9O2bfxiBsH1r`

Country	Sample size	Share of total
Germany	2161 obs.	26.24%
Italy	2003 obs.	24.32%
Netherlands	2071 obs.	25.15%
Spain	2000 obs.	24.29%
Total	8235 obs.	100.00%

Table 1: Sample size per country

The survey flow was structured as follows:

Background information Gender, age, marital status, household size (number of adults and number of children), household monthly disposable income.

Socio-political attitudes block (outcome questions) We ask respondents about a wide range of their socio-political attitudes, the outcome questions of our survey. These questions can be grouped into four different dimensions summarised below: trust, taxation, voting and EU preferences, identity and values. A complete list of the outcome questions can be found in Table 2.

> **Trust** These questions cover the respondents' generalised and particular trust attitudes towards society, institutions (national government and European Union) and political leaders, science, the media and the police.
>
> **Taxation** The respondents are asked to state their level of support for various forms of state economic intervention. These include support for generic market intervention, for redistributive taxation, use of public health systems and whether they feel their own and the general tax burden in their country is excessive.
>
> **Voting and EU preferences** We elicit both voting intentions and political attitudes. We then use voting intentions to classify the respondents according to whether they would, in hypothetical elections, support incumbent governments, populist or eurosceptic parties. Among the political attitudes we elicit their placement on the left-right spectrum, whether they perceived the EU to have been beneficial for their country, their preference for a strong leader, for devolution of political powers to the citizens and their support for civil and political liberties.

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Identity and values This dimension covers the respondents' perceived belonging and identification with various geopolitical reference areas, ranging from local to supranational (European). We moreover elicit the respondents' willingness to trade-off their own private freedom for the sake of their own safety, that of their immediate relations and of the general public. Finally, they provide their trade-off between universal and traditional values and their preference for globalization of markets.

COVID-19 block (treatment questions) The respondents receive a range of questions concerning the COVID-19 epidemic and its consequences. These were divided into three categories.

Health We ask the respondents which of the commonly recommended behaviours to contain the spread (e.g. social distancing, disinfection, testing) respondents have adopted, whether they had COVID-19 cases among their acquaintances and family members, and whether they were concerned for their health and for that of those around them. Notice that while labeling this category "Health" these questions are intended to elicit the respondents' basic day-to-day experience of the COVID-19 epidemic rather than its strictly medical aspects.

Economic We here elicit how the respondents perceive the economic consequences of the epidemic, whether they were impacted themselves in terms of job loss and future job opportunities.

Conflict Finally, we ask whether the respondents perceive the COVID-19 epidemic as a conflict against an invisible enemy and whether they perceive unity and national solidarity as the main "winning" strategies.

Further background information Highest educational attainment, primary information sources, employment status, immigration background, political beliefs and voting behaviour.

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Category	Outcome variables	Label
Trust	Text agreement question (behavioural outcome)	Macron Speech
	Trust in politicians	Trust Politicians
	Generalised social trust	Social trust
	Trust in the Government	Trust Government
	Trust in the Police	Trust Police
	Trust in the Media	Trust Media
	Trust in Science	Trust Science
	Trust in the European Union	Trust EU
Taxation	Market regulation	Regulate Markets
	Taxation for poverty relief	+Taxes - Poverty
	Taxation for public health provision	+ Taxes + Health Exp.
	Taxation for income replacement in unemployment	+ Taxes + Unemployed Welfare
	Taxation for income replacement in old age	+Taxes + Pensions
	Preference over current immigration level	Too Many Immigrants
	Attitudes towards public healthcare access for immigrants	Health Exp. to Natives
	Perceived overall fiscal burden	General Tax Too High
	Perceived own fiscal burden	Self Tax Too High
Voting & EU preferences	Incumbent vote	Incumbent Voting
	Populist vote	Populist Voting
	Euroscept. vote	Eurosceptic Voting
	Placement in political spectrum	Ideology (Left to Right)
	Perceived benefit of the EU	EU Benefit
	Perceived efficacy of the EU	EU Efficacy
	Would vote to leave the EU	Leave EU
	Prefers a strong leader	Strong Leader
	Preference for privacy protection	More Privacy
	Attitudes towards placing power in the people's hands	People Power
	Preference for media freedom	Free Media
	Is convinced plutocracies control politics	Plutocracy
Identity & values	Sense of local belonging	Belong Town
	Sense of national belonging	Belong Nation
	Sense of European belonging	Belong EU
	Would give up personal freedom to protect own safety	- Own Freedom + Own Safety
	Would give up personal freedom to protect family's safety	- Own Freedom + Family Safety
	Would give up personal freedom to protect public safety	- Own Freedom + Public Safety
	Upholds global human rights	Global Human Rights
	Upholds respect of local traditions	Respect Traditions
	Would have less globalisation	Less Globalisation

Table 2: List of outcome variables by category

2.1 Incentivised willingness to support European integration

In order to better capture how the respondents' attitudes towards the European Union are impacted by the epidemic and its various dimensions, the socio-political attitudes block includes an incentivised behavioural measure of their willingness to engage in an action explicitly framed as supportive of the European integration project. The respondents are told that:

> "For educational purposes, we are considering informing students about the importance of the European Union using real texts. We selected a speech given in front of the European Parliament promoting European integration."[10,11]

We then ask the respondents whether they would be willing to read a five-minute long transcription of the speech and to give us their opinion about the suitability of the text for the purpose it was selected for. This way we provide a clear incentive to respondents who are *not willing* to spend five minutes of time (it took on average approximately 20 minutes to complete the survey *without* reading the text) reading a pro-European Union text and to provide their opinion, to decline (see also Dellavigna et al. (2017)). We explicitly fixed the amount of time needed to read the speech in order to fix beliefs about the length of the task and the amount of time and effort needed to complete it. Further, the explicit reference to the educational usage of the text (in a Public Economics undergraduate course at the University of Stirling taught by one of the authors) serves the purpose of providing the respondents with a sense of consequentiality of the action and effort invested in it. The identity of the speaker and the context in which the speech was given (apart from it being addressed to the EU Parliament) was not disclosed to the respondents at the time of choosing whether to read the text or not. We also informed the respondents that their agreement or lack thereof will not affect their payment. In case of agreement, the respondents are told that they will read and review the text only at the very end of the survey.[12]

We interpret the respondents' choice of (not) reading the text and providing their opinion on its suitability for the stated purpose as (un)willingness to support the European integration and *not* the rating provided. It might very well be the case that a respondent with extremely positive attitudes towards the European integration might legitimately find the text unsuitable for the purpose and assign it a low rating. A non-trivial choice was whether to explicitly frame the action as supportive of European integration or whether to maintain a more neutral wording (e.g. by removing the word "importance" and replacing "promoting" with a neutral "about the" in the quoted text

[10] See Appendix F for an English transcription of the whole question.

[11] An English transcription of the original speech can be found at the following link: https://www.elysee.fr/emmanuel-macron/2018/04/17/speech-by-emmanuel-macron-president-of-the-republic-at-european-parliament.en

[12] A discussion of the experimental challenges posed by this question and of how they are here addressed can be found in Section 3.1.

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above). Had we chosen the neutral wording, however, the interpretation of the agreement to read the text would have not been straightforward. As argued above, framing it as pro-integration allows for a combination of agreement to read and low-rating assigned to still be interpretable as supportive of the European integration. This would not have been the case with neutral wording, as a respondent antagonising the integration process could have agreed to read the text with the mere intent of assigning a low score. It can be argued that our behavioural measure of support for the European integration could have in such case been the rating distribution. Notice however that those choosing not to read the text would have been dropped out of the analysis and that the incentivisation would have been lost (it is costly to choose to spend five more minutes to read but it is costless to assign the rating). Our choice does not completely exclude the possibility that the respondents might accept to read and then assign ratings without reading. The incidence of such behaviours is however likely to be orthogonal to our experimental design and smaller than with neutral wording. Our choice moreover allows us to perform analyses allowing us to gauge the validity of the responses collected and of our behavioural measure.

The analyses presented in Appendix E confirm the validity of our behavioural measure and our interpretation. In order to perform such analyses, we recorded the time spent by the respondents between accessing the text and moving on to the following page. This way we are able to discriminate between respondents who, after agreeing to reading the text, only provide their opinion without actually investing any effort and to relate the time spent on the question with the ratings provided (a ten-step numeric variable). We thus gain an insight into the attitudes towards the European integration process of those who agree to read, and into the systematic differences in the distribution of such responses across experimental conditions.

3 Experimental Design

Our design consists of two main experimental conditions: A Baseline condition in which the respondents provide their unprimed answers to our target questions, and a COVID-FIRST condition in which the respondents provide instead their answers to our target questions after having been primed with various aspects of the COVID-19 crisis. This means that participants in the Baseline condition answer the survey in the order described in Section 2, whereas for participants in the COVIDFIRST condition the order

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of the Socio-political attitudes block and the COVID-19 block is switched.[13]

Further, as detailed in Section 2, the COVIDFIRST condition is divided into three "sub-conditions" meant to delve deeper into the mechanisms at play. Specifically, all respondents receive questions about their perceptions of and behaviours in relation to the COVID-19 epidemic as a health crisis. The respondents are then divided into three mutually exclusive groups. A first group is not subject to any further intervention. We will henceforth refer to this group as to the Health condition. A second group which we will henceforth refer to as the Economic condition receives a set of questions emphasising the economic consequences of the COVID-19 crisis *in addition* to the health related questions. Finally, a third group which we will refer to as the Conflict condition receives (again in addition to the health questions) a set of questions mimicking the conflict rhetoric often used in relation to the epidemic and emphasising the explicit need for social solidarity in winning the "war against the invisible enemy". Summarising, while all respondents in COVIDFIRST receive the COVID-19 block of questions before the socio-political attitudes block, we randomise whether and which of the economic and conflict dimension of the epidemic are emphasised by the questions. The experimental design is summarised in Table 3.

Baseline	**COVIDFIRST**
Background information	Background information
Socio-political attitudes block (outcomes)	COVID-19 block Presented with one of: Health Health + Economic Health + Conflict
COVID-19 block Presented with one of: Health Health + Economic Health + Conflict	Socio-political attitudes block (outcomes)
Further background information	Further background information

Table 3: Summary of the experimental design

[13]See Alesina et al. (2018) for another example of the use of this strategy of randomizing the order of survey blocks.

Worth mentioning is that this design allows us to better disentangle the impacts of the economic and of the conflict dimensions of the epidemic from those of the pure health dimension than it would have been if all three dimensions were assigned exclusive groups of respondents. The COVID-19 crisis is *primarily* a health crisis which also bears consequences and implications on the economy and more generally on society. Exposing respondents to the, for instance, economic consequences of the crisis exclusively does not exclude the activation of some degree of health-related concerns over which the researcher has no control. Conversely, explicitly activating the health dimension in all conditions in the same way as in the Health condition allows us to take the health component as fixed and to cleanly identify the impact of the other dimension being activated.

Respondents assigned to the Baseline condition are exposed to the same sub-conditions (health, health and economic, health and conflict) as respondents in the COVIDFIRST condition. The sub-conditions are however expected to have no impact on the answers provided in the outcomes block in the Baseline condition, as the treatment questions come later in the survey flow. Placebo tests performed on these respondents are presented in Appendix C.2.

3.1 Further considerations

We identify two primary potential confounds in our experimental design.

Fatigue Fatigue might influence the propensity to choosing to review our text on European integration. To see this, remember that we randomize whether the outcome variable questions come before or after the questions about the COVID-19 crisis. Half of the respondents will receive the question on whether they wish to read a lengthy text (explicitly fixed at 5 minutes of time) about the European integration relatively early in the survey, while half will receive it relatively late. Among the latter, greater fatigue is expected to decrease the likelihood of agreement. Fatigue would therefore cause us to over-estimate a negative impact of the COVIDFIRST condition, which is why we treat it as a confound deserving high priority.

The position of the text agreement question is therefore randomly placed at the beginning or at the end of the outcomes block: its placement varies between early on, somewhat in the middle and towards the end of the entire survey, orthogonally to the experimental conditions. Moreover, in case of agreement, the respondents will read the

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text and provide their opinion at the end of the questionnaire to shield the following parts of the survey from additional fatigue originating from the text review task.

Experimenter demand effects Participants to surveys or experiments might infer the researchers' underlying objectives from the questions asked and/or from the experiment's architecture, and act to comply with what they believe are the experimenter's objectives Zizzo (2010). In our case, a respondent might form an idea that our ultimate objective is that of measuring socio-political sentiments, particularly towards the EU, from the questions we asked. Demand effects might bias our respondents' answers in uncontrollable ways, thus reducing the likelihood of observing the effects of interest.

We cannot address this concern directly, as we must tradeoff between reaching our research objectives and eliminating the risk of demand effects. We however are able to evaluate the likelihood of demand effects polluting our questionnaire by exploiting the randomization of the position of the text agreement question. The explicit pro-EU sentiment in that question leads to a strengthened pro-EU demand effect affecting subsequent questions beyond the natural demand induced by the questionnaire itself de Quidt et al. (2018). Comparing the responses of those exposed to strengthened demand effects at the beginning and at the end of the outcomes block allow us to establish whether the survey is susceptible to any demand effect originating from the questionnaire itself.[14]

4 Statistical Models and Analyses

At a first level, we evaluate the overall impact on the respondents' socio-political attitudes of answering the COVID-19 block first. We therefore estimate the following OLS model:

$$Y = \beta_0 + \beta_1 COVIDFIRST + \beta_2 X + \beta_3 W + \beta_4 \kappa + \varepsilon, \tag{1}$$

where Y is the vector of answers from the socio-political attitudes block, COVIDFIRST is equal to 1 if the respondent answered the COVID-19 questions first and zero otherwise, X and W are respectively vectors of individual and regional covariates, and κ denotes country fixed effects. We cluster the standard errors at the province level (NUTS-3).[15]

[14] Appendix C.1 shows no evidence for demand effects originating from the text agreement question.
[15] Our results are unchanged by usage of different clustering levels.

We further delve deeper into the analysis of the mechanisms behind the effect of the epidemic on our respondents' socio-political attitudes by evaluating the additional impact of the economic crisis and conflict dimensions of the epidemic beyond the health hazard dimension. Section 3 illustrates the experimental strategy we adopted to achieve this objective. As there explained, we fix the health dimension across sub-conditions and use it as a baseline to treat the respondents with their everyday experience with the COVID-19 epidemic with the aim of evaluating the further impact of the economic and conflict dimensions. Our statistical strategy is reflective of this approach. For simplicity, construct a categorical variable denoted T taking values

$$T = \begin{cases} 0 & if \quad COVIDFIRST = 0 \\ 1 & if \quad COVIDFIRST = 1 \quad and \quad \text{Health condition} \\ 2 & if \quad COVIDFIRST = 1 \quad and \quad \text{Economic condition} \\ 3 & if \quad COVIDFIRST = 1 \quad and \quad \text{Conflict condition.} \end{cases}$$

In a first step at deepening our analysis, we therefore establish the baseline effect of on socio-political attitudes of experiencing a health crisis by restricting model (1) to the Baseline and Health condition only:

$$Y = \beta_0 + \beta_1 T + \beta_2 X + \beta_3 W + \beta_4 \kappa + \varepsilon, \quad T = \{0, 1\}. \tag{2}$$

We next evaluate the additional impact of the economic and of the conflict aspects of the COVID-19 epidemic beyond the health hazard. Remember that the Economic and Conflict conditions *add* questions concerning to the economic and conflict dimensions of the epidemic to the health related questions already included in the Health condition. We therefore take the outcomes measured in the Health condition of the COVIDFIRST treatment as the baseline estimates for two additional models, ultimately measuring the impact of adding the economic or conflict dimensions to the health baseline. The first model concerns the economic dimension:

$$Y = \beta_0 + \beta_1 T + \beta_2 X + \beta_3 W + \beta_4 \kappa + \varepsilon, \quad T = \{1, 2\}. \tag{3}$$

Notice that as COVIDFIRST (the indicator taking value 1 if the respondent answered the COVID-19 block before the outcomes block) is fixed to 1 and T is constrained to taking values 1 and 2, β_1 can be interpreted as the impact of having answered the questions in the Economic condition compared to having answered the questions in the Health condition among respondents who answered the COVID-19 question block first.

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An analogous model is estimated to evaluate the impact of the Conflict condition:

$$Y = \beta_0 + \beta_1 T + \beta_2 X + \beta_3 W + \beta_4 \kappa + \varepsilon, \quad T = \{1, 3\}. \tag{4}$$

To ease the interpretation of our results, all outcome variables have been standardised with respect to the outcomes in Baseline.

All regressions control for gender, age class, employment status, education, immigrant status, family status and number of family members, equivalised household income (coded into five quantiles), and a dummy indicating the position of the Macron Speech question (see Section 3.1 for more details).

5 Results

5.1 Aggregate Analyses

In this section we report the estimates of model (1) on the entire sample. In Figure 1, we compare all treated individuals (COVIDFIRST) with the Baseline group. In this first specification, we therefore do not differentiate across health, economic and conflict sub-condition groups. The analysis is organized around our four blocks of outcomes: a) trust, b) taxation, c) voting and EU preferences and d) identity and values. All outcomes have been standardised with respect to the Baseline group. All coefficients should hence be interpreted relative the unit standard deviation (SD) of the Baseline.

Figure 1 provides strong evidence about the impact of COVIDFIRST across different sets of outcomes. We report the estimated coefficients in Appendix B. First, we find very heterogeneous effects on trust. The COVID-19 treatment has a negative and statistically significant effect on social trust (-0.13 SD), trust in media (-0.08 SD), trust in politicians (-0.04 SD) and trust in the European Union (-0.12 SD). There is no effect on trust in government. Conversely, we find a positive and significant effect on trust in police (+0.08 SD) and science (+0.09 SD). In line with a negative effect on EU attitudes, the incentivised behavioral outcome, i.e. being willing to read a pro-EU speech for educational purposes, reports a strongly negative and statistically significant coefficient (-0.14 SD). Indeed, the bottom panels report similar findings related to the EU: the bottom left panel shows a significant decrease in perceived EU efficacy (-0.10 SD) and benefit (-0.10 SD); the bottom right one reports a negative effect on EU identity (-0.08 SD). These heterogeneous effects might underlie different evaluations on the performance

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of such institutions in the face of the COVID-19 crisis, which then affect their level of perceived trustworthiness.

Second, the top right panel shows a consistently negative effect on attitudes towards levying taxes to finance the welfare state. This is true for poverty alleviation (-0.10 SD), health expenditure (-0.07 SD), unemployment benefits (-0.06 SD) and pensions (-0.07 SD).[16] In line with these findings, respondents in COVIDFIRST report that their fiscal burden is too high (0.06 SD). These findings show that priming people about COVID-19 decreases willingness to finance the welfare state, in a time in which politicians are pressured to tremendously increase welfare expenditure to deal with the health crisis and an economic downturn. As mentioned in Section 1, a 'disillusion' effect towards institutions and fellow citizens might explain why we find a decreased willingness to pay into the redistributive system.

Third, we find some evidence of a negative effect on populist attitudes (bottom left panel) in terms of preferring a strong leader (-0.05 SD) and allowing people to make the most important policy decisions (-0.05 SD). However, we do not find any effect on voting preferences. Similarly, the bottom right panel shows no conclusive evidence of an effect on self-reported values and attitudes towards freedom and public safety.

In Appendix A, Figures A1, A2, A3 and A4 display the results from country-level analyses. Overall, the effects are strikingly similar across Germany, Italy and the Netherlands. Spain seems however to stand out, as both the effects on trust and welfare preferences seem to be attenuated. First, we do not find a clear decrease in trust for institutions, as there is not a significant decrease in trust for media and politicians. In terms of EU attitudes, while COVIDFIRST decreases trust in the European Union, it does not substantially affect other EU related outcomes, like EU benefit, EU efficacy and attachment towards the EU. On the other hand, we do not find a clear decrease in preferences towards levying taxes. We further discuss the Spanish case in the next section.

[16] Interestingly, we find a negative effect on whether the public health care system should prioritize locals over immigrants.

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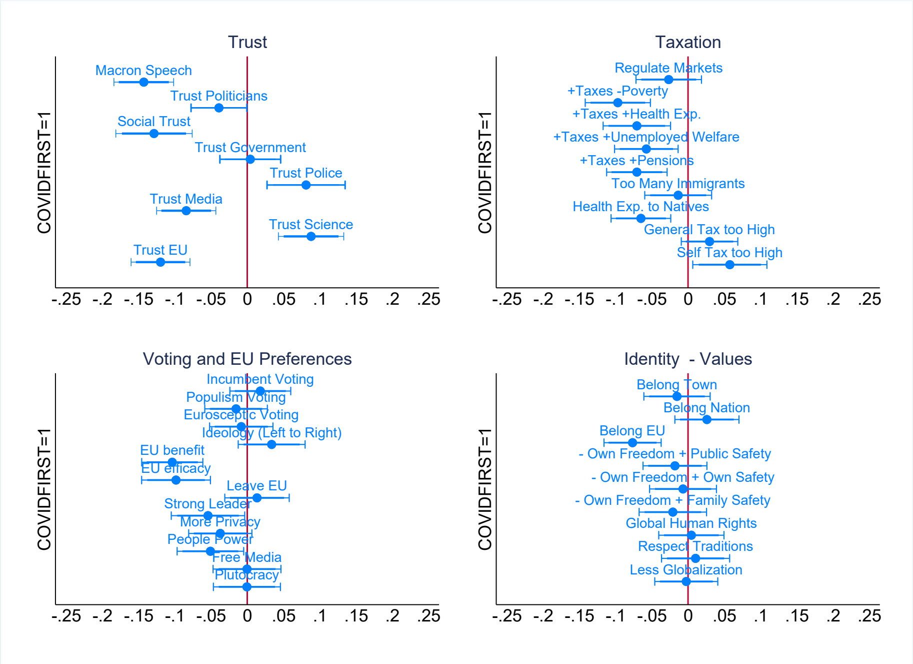
Figure 1: Effect of COVID-19 priming (Entire sample)



The figure shows the impact of COVIDFIRST on the four set of socio-political outcomes. For each coefficient, 95% (delimited by horizontal bars) and 90% (bold line) confidence intervals are shown.

5.2 Economic dimension and 'rally around the flag'

We now investigate how the three different health, economic and conflict sub-conditions differently contribute to the results presented in Section 5.1 to shed light on the mechanisms underlying our findings. In Figure 2, we first look at the effects of receiving questions highlighting only the health dimension of the crisis by only being asked about the health related experience of the COVID-19 epidemic. In this case, the comparison is with the Baseline group (i.e. individuals receiving outcome questions first, after which COVID-19 -related questions follow) as of model (2). The findings are mostly similar to the ones presented in Figure 1 with some exceptions: i) we do not find a negative effect on attitudes towards the individual fiscal burden; ii) we do not find any effect on populist attitudes; iii) we find a positive effect on support for political parties in

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the national government. These observations suggest that at least some of our findings are driven by the sub-treatments eliciting the economic and 'conflict' dimensions of the COVID-19 crisis.

In Figure 3, we focus on the effect of the economic dimension of the crisis. As already explained in Section 3, we add the economic dimension to the health. As of model (3), the comparison is between individuals receiving the Economic condition with those only receiving the Health condition. The latter thus serve as a baseline comparison. First, the economic condition appears to consistently shift trust attitudes to the left: the estimated coefficients are all negative, many significant at conventional levels. In line with a sharper decrease in trust towards institutions, we find lower attitudes towards giving up freedom in exchange for individual and public safety (bottom right panel). Second, in contrast with what was observed in the Health condition, individual and general tax burdens are perceived as excessive when the economic dimension of the COVID-19 epidemic is emphasised. Third, the bottom left panel shows a negative significant effect on support for incumbent parties and a negative (barely not statistically significant) effect on support for populist and Eurosceptic parties.

Figure 4 displays how the rhetoric highlighted in the Conflict sub-treatment impacts socio-political attitudes beyond the Health condition: in this case, the comparison is between individuals receiving Conflict condition with those receiving the Health condition as a baseline. Our focus here is on the 'rally around the flag' effect stressed by the media and politicians in the weeks immediately after the arrival of the epidemic in Europe. This condition shows remarkably little impact beyond that of the health intervention. The only striking difference concerns trust in science, as the conflict dimension has a much more positive effect than the simple health dimension (0.20 of a SD).

Overall, the results in this section show that the economic dimension seems to trigger additional and negative responses in terms of trust and welfare support, as well as in terms of approval for the ruling political parties. Conversely, the 'rally around the flag' treatment has limited effects in addition to the health dimension (except for trust in science).

As highlighted in the previous section, our findings of a 'disillusion' effect are attenuated among Spanish respondents. A possible explanation is that a positive 'rally around the flag' effect prevailed in this case. This is indeed what we find when we compare the effects of the conflict condition (Figure 4), distinguishing between Spain and the

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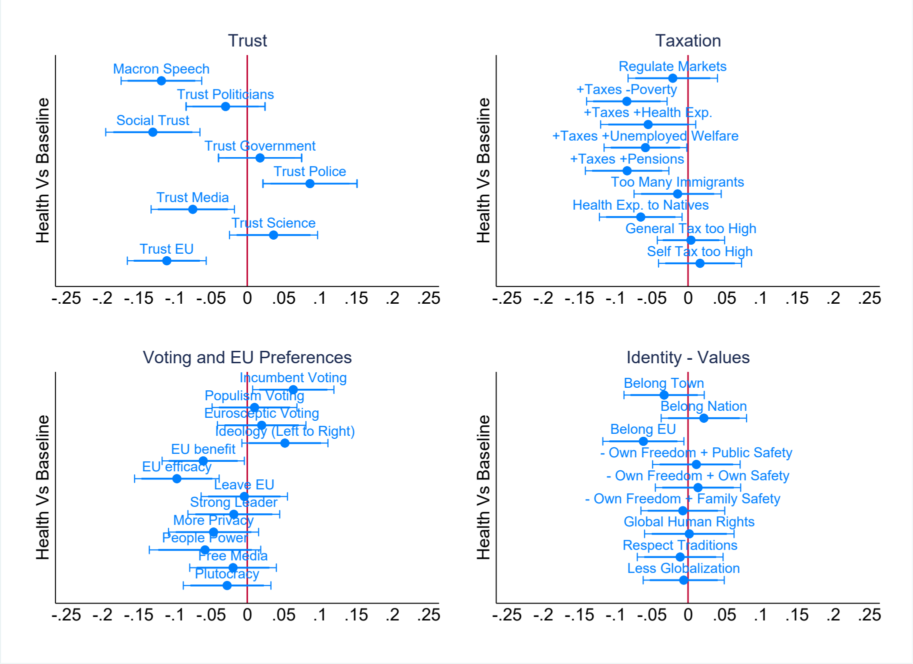
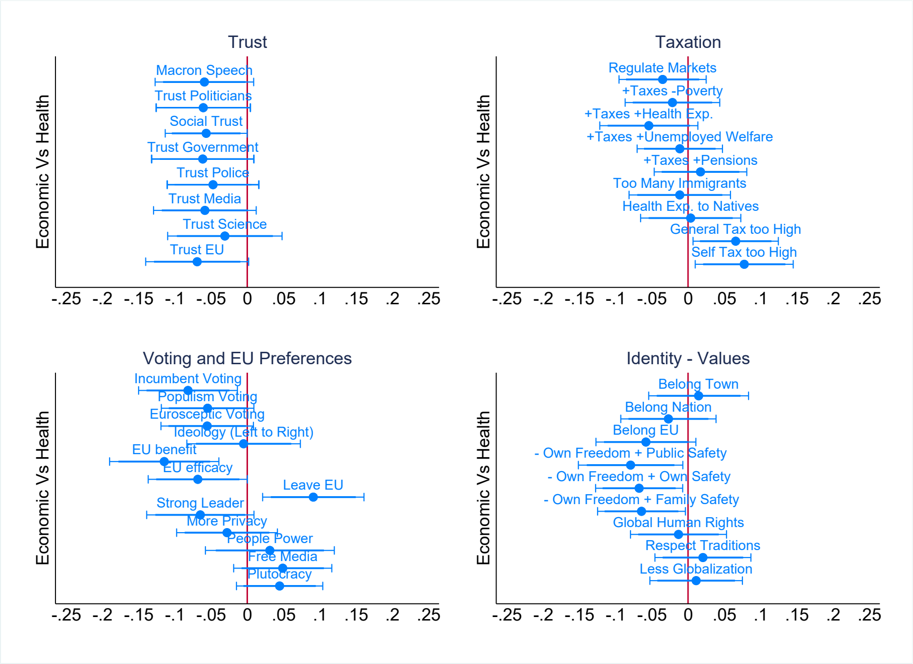
other three countries. Appendix Figure A5 shows very weak effects of this condition in Germany, Italy and the Netherlands; conversely, Appendix Figure A6 shows remarkably strong effects in Spain, in terms of i) general higher levels of trust (with a massive effect on trust in science, 0.40 of a SD) and EU preferences; ii) stronger attitudes of belonging to local, national and supra-national communities; iii) and higher demand for privacy and traditional values.

Figure 2: Effect of the Health condition compared to C



The figure shows the impact of the Health condition (COVID-19 health treatment) on the four set of socio-political outcomes. For each coefficient, 95% (delimited by horizontal bars) and 90% (bold line) confidence intervals are shown.

Figure 3: Effect of the Economic condition compared to the Health condition



The figure shows the impact of the Economic condition (economic effects of COVID-19) compared to the Health condition (COVID-19 health treatment) on the four set of socio-political outcomes. For each coefficient, 95% (delimited by horizontal bars) and 90% (bold line) confidence intervals are shown.

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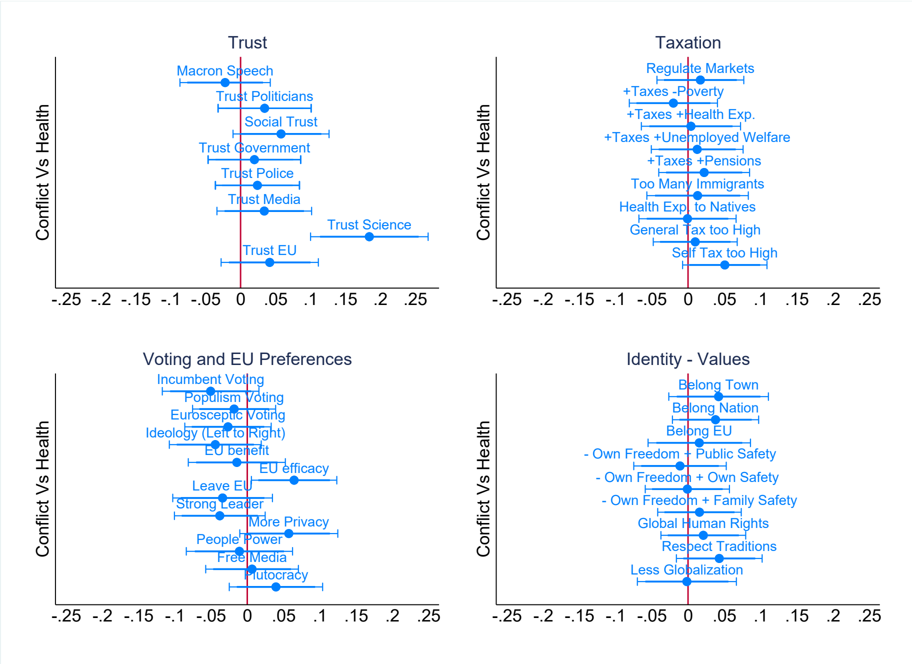
Figure 4: Effect of the Conflict condition compared to the Health condition



The figure shows the impact of the Conflict condition ('rally around the flag') compared to the Health condition (COVID-19 health treatment) on the four set of socio-political outcomes. For each coefficient, 95% (delimited by horizontal bars) and 90% (bold line) confidence intervals are shown.

5.3 COVID-19 and European's willingness to support the European Union

It is worth spending some time on the performance of the behavioural (incentivised) measure of our respondents' willingness to engage in an action explicitly framed as supportive of European integration and its interpretation. As described in Section 3, the question "Macron Speech" asked the respondents whether they would be willing to spend five minutes of their time to read and review a text about the European integration process. As shown in Figure 1 a significantly lower proportion of respondents agrees to read the text when asked. We interpret this finding as evidence that focusing the respondents attention on the COVID-19 epidemic and on its dimensions here investigated leads to a decreased willingness to engage in an action supportive of European integration. In

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support of this interpretation, we present investigations of the behavioural regularities associated with the choice to read the text in Appendix E.

The results presented in Appendix E give us an indication that our behavioural outcome indeed captures a clean measure of willingness to engage in an action framed as supportive of the European integration process. We find no meaningful differences in the amount of time spent on the text screen and no differences in the distribution of scores assigned to the text across conditions and a weak though significant relationship between the amount of time spent on the text screen and the rating to it assigned by the respondent. We are therefore confident that the impacts of our conditions on the willingness to read and review the text are orthogonal to the respondents' underlying attitudes towards the European integration project.

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5.4 Real and perceived exposure to COVID-19 and compliance with lock-down rules

As explained in Section 3, our baseline treatment includes an array of questions related to individuals' exposure to and experience of the COVID-19 epidemic (see Appendix F for the English questionnaire). In this section, we focus on the heterogeneous effects in regard to individuals' experiences with the COVID-19 19 and lockdown measures. These questions were by design asked to all the respondents in our study. We are interested in studying whether our findings are systematically heterogeneous with respect to individuals' experience with the COVID-19 epidemic.

These experiences can be divided into three groups: i) having contracted the virus or having someone close who has contracted the virus; ii) the individuals' level of compliance with the lock-down laws; and iii) the level of concern in relation to the virus.[17] We label these groups *Contracted*, *Compliance* and *Concerned* respectively. For each group, we include all relevant questions in a factor analysis revealing the presence of a single factor upon which all elements load strongly (i.e. all factor loadings exceed 0.61). Each factor can be interpreted as a single variable summarising the information contained in each underlying variable. The factor variables are therefore increasing in whether someone: i) has contracted the virus and/or know someone who has contracted the virus; ii) has

[17]Specifically, i) includes questions on whether the respondent, someone in his/her family or someone (s)he knows, has contracted the virus; ii) includes replies on whether the respondent perceived social distancing rules as being too strict, kept social distancing and wore a mask; iii) includes statements on whether the respondent tried to get tested for COVID-19 and his/her self-reported level of concern about his/her health.

complied with the lock-down rules; and iii) reports to be worried about the virus.[18]

The factor variable predicted values are then employed in the analysis of how the impact of COVIDFIRST varies along the *Compliance*, *Concerned* and *Contracted* dimensions.[19] In Figures 5, 6 and 7 we report the results, which only display the interacted coefficients.

Figure 5 focuses on the interaction between COVIDFIRST and the level of compliance with the lock-down measures. Treated individuals with higher levels of compliance are more likely to trust institutions (i.e. politicians, the government and science) and perceive their individual and the general tax burden as less problematic, while they trust other people less. The former could again be interpreted as a proxy of the 'rally around the flag' effect, in the form of cooperation with the government and a higher approval of the policy implemented to counter the health crisis. The latter effect could be because those respecting the rules the most also perceive others around them as respecting the rules less, so that the relational and conditional nature of trust – as described by Levi and Stoker (2000) – is eroded.

Among those who are concerned about their health, a similar argument can be made. Figure 6 shows that *Concerned* $\times$ COVIDFIRST slightly boosts levels of institutional trust as well, but mostly marks remarkably higher support for taxation and welfare programs, as well as market regulation. Social trust is lower also for this group, which is possibly due to mounting stress levels as pointed out by Potts et al. (2019).

From Figure 7 we learn that *Contracted* $\times$ COVIDFIRST leads to similar conclusions for those who have been in close contact with the virus, with a significantly higher support to raise taxes to finance public health expenditure. A remarkable exception is the neutral effect on social trust. This could mean that perceived risk plays a bigger part in trusting others, rather than actual 'realised' risks of catching the virus, as also argued by Brück et al. (2020).

[18]Details about the factor analyses can be found in Appendix D.

[19]Tables B33 to B44 in Appendix B.4 shows that the replies to the questions included into *Compliance*, *Concerned* and *Contracted*, and are exogenous to the COVIDFIRST condition.

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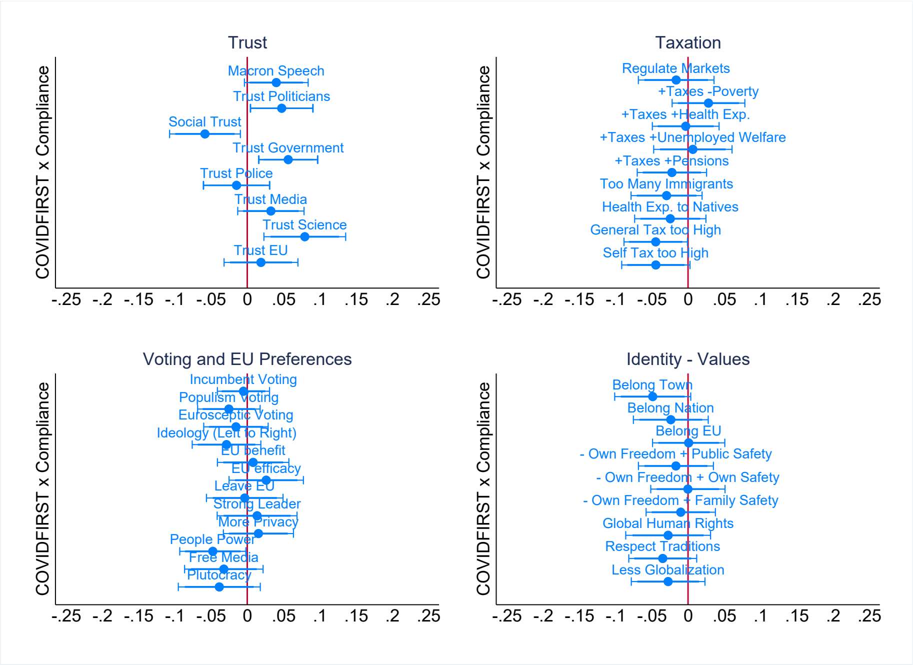
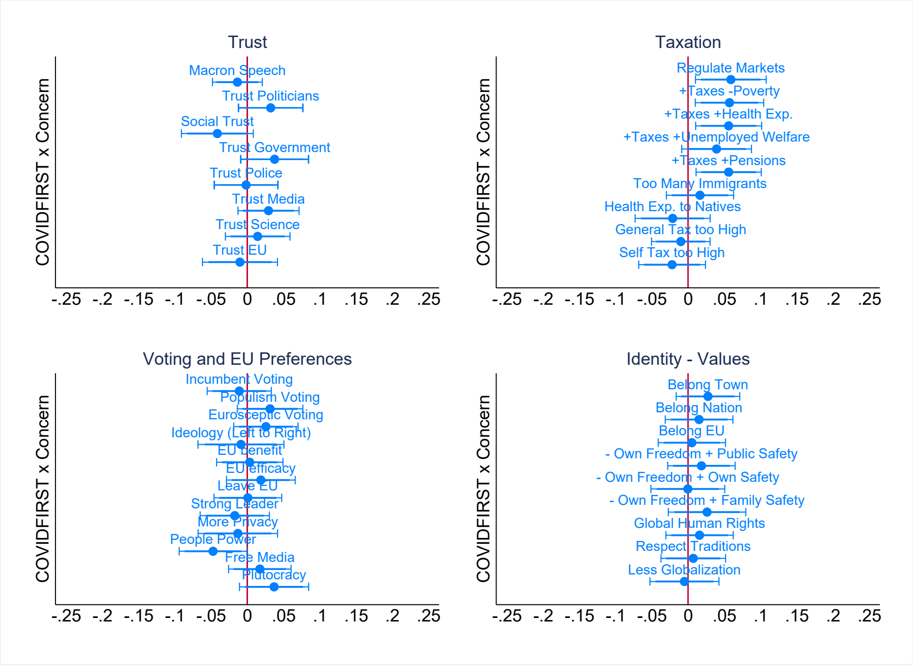
Figure 5: Interaction effects: compliance



The figure shows the impact of the interaction $COVIDFIRST \times Compliance$ on the four set of socio-political outcomes. For each coefficient, 95% (delimited by horizontal bars) and 90% (bold line) confidence intervals are shown.

Figure 6: Interaction effects: health concerns



The figure shows the impact of the interaction $COVIDFIRST \times Concern$ on the four set of socio-political outcomes. For each coefficient, 95% (delimited by horizontal bars) and 90% (bold line) confidence intervals are shown.

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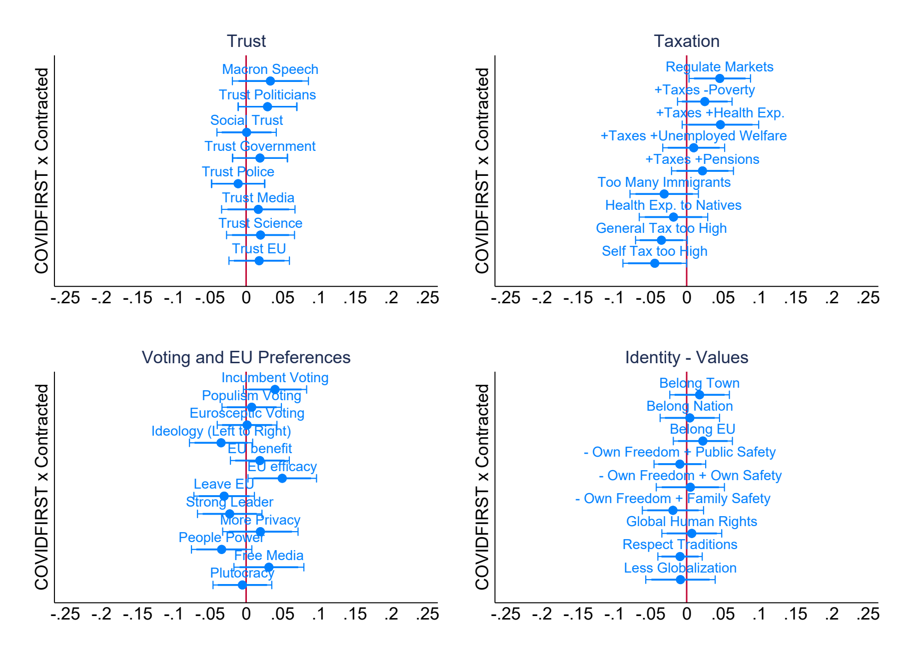
Figure 7: Interaction effects: exposure to the virus



The figure shows the impact of the interaction $COVIDFIRST \times Contracted$ on the four set of socio-political outcomes. For each coefficient, 95% (delimited by horizontal bars) and 90% (bold line) confidence intervals are shown.

6 Conclusions

In this paper we show that simply priming people to think about COVID-19 can shape their socio-political attitudes. More specifically, their view about their government, their politics, their institutions in general as well as the design of their welfare state seem to be affected, along with many other dimensions of their (political) life. We do so by randomising the order in which a block of survey questions – eliciting people's experience with the COVID-19 crisis – are posed, as opposed to a block of questions eliciting their political attitudes.

We find significant treatment effects in all of our outcome categories, indicating that the crisis has brought about severe drops in interpersonal and institutional trust, as well as lower support for the EU and social welfare spending financed by taxes. We also found

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that priming with the purely economic effects of the crisis shapes people's attitudes quite differently than priming only on the health or 'conflict' dimensions of the pandemic, with lower levels of institutional support and trust compounded by economic insecurity. A rallying effect around (scientific) expertise combined with populist policies losing ground forms the other side of this coin, and hints at a rising demand for competent leadership.

Of course, our results should first and foremost be interpreted as a shock, diverging from existing trends. Whether we have in fact uncovered a critical juncture setting these trends on an entirely different path, can only be ascertained by conducting follow-up waves of our survey experiment. Depending on how governments will manage the economic recovery and/or a possible resurgence of the virus will be a crucial factor here. In any case it will be interesting to see whether the rising demand for competent leaders and policies we uncover is met in the future, or whether the 'disillusion' effect our study also brings to the surface will eventually be channeled into increased populist support if the opportunity is missed.

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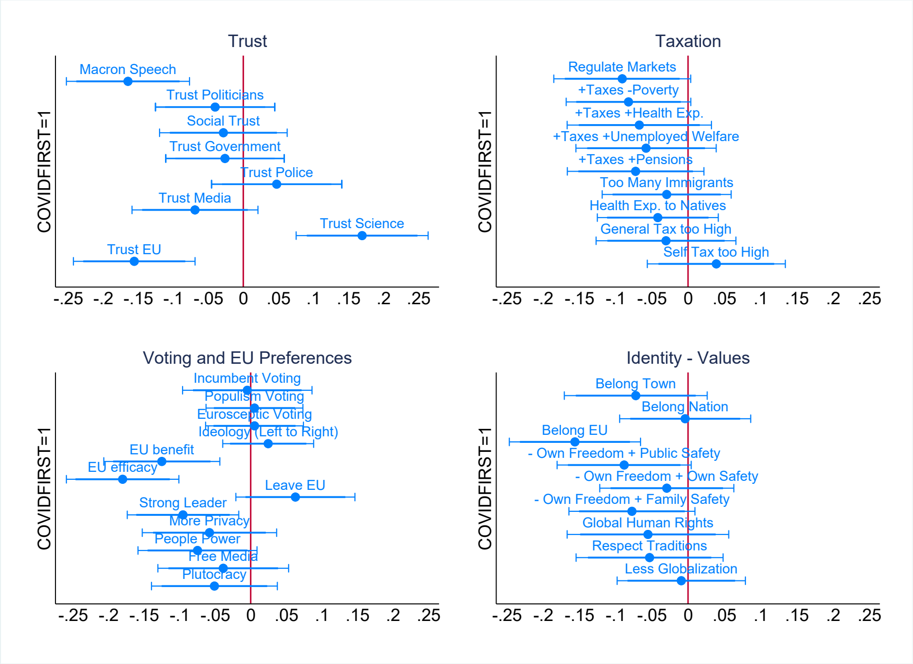
Appendix

A Results by country

Figure A1: Effect of the intervention in Germany



The figure shows the impact of COVIDFIRST on the four set of socio-political outcomes in Germany. For each coefficient, 95% (delimited by horizontal bars) and 90% (bold line) confidence intervals are shown.

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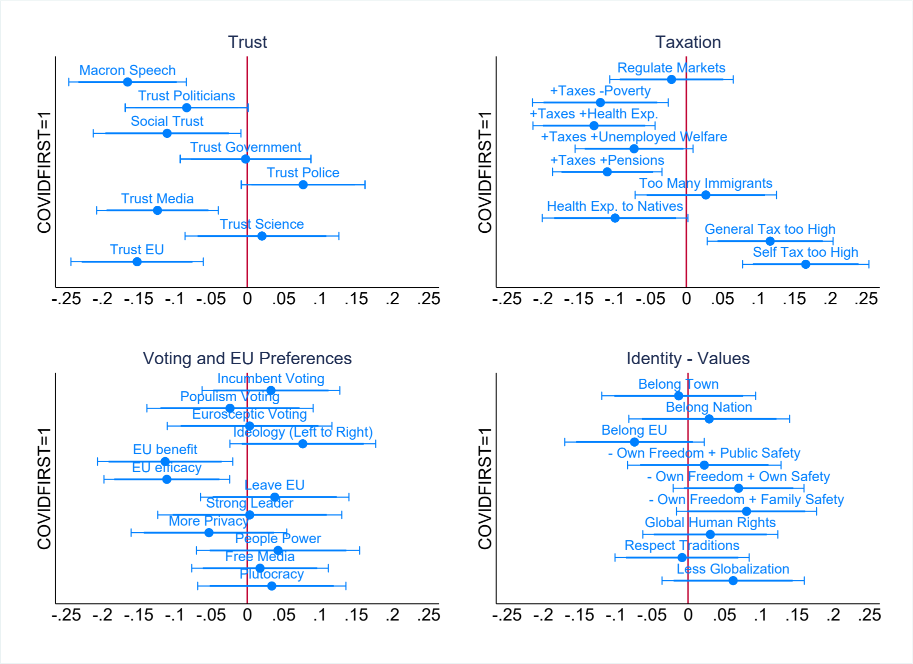
Figure A2: Effect of the intervention in Italy



The figure shows the impact of COVIDFIRST on the four set of socio-political outcomes in Italy. For each coefficient, 95% (delimited by horizontal bars) and 90% (bold line) confidence intervals are shown.

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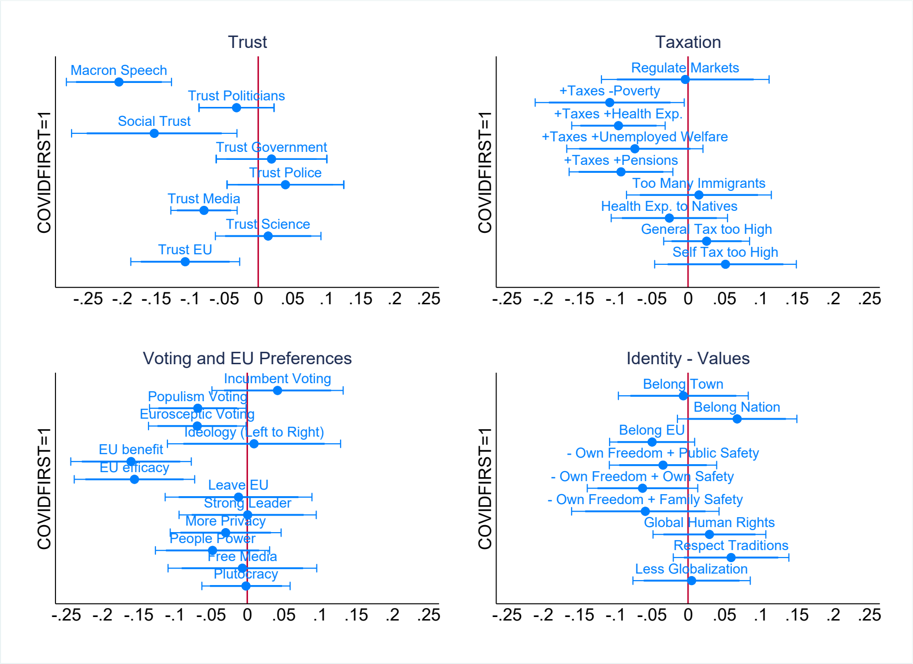
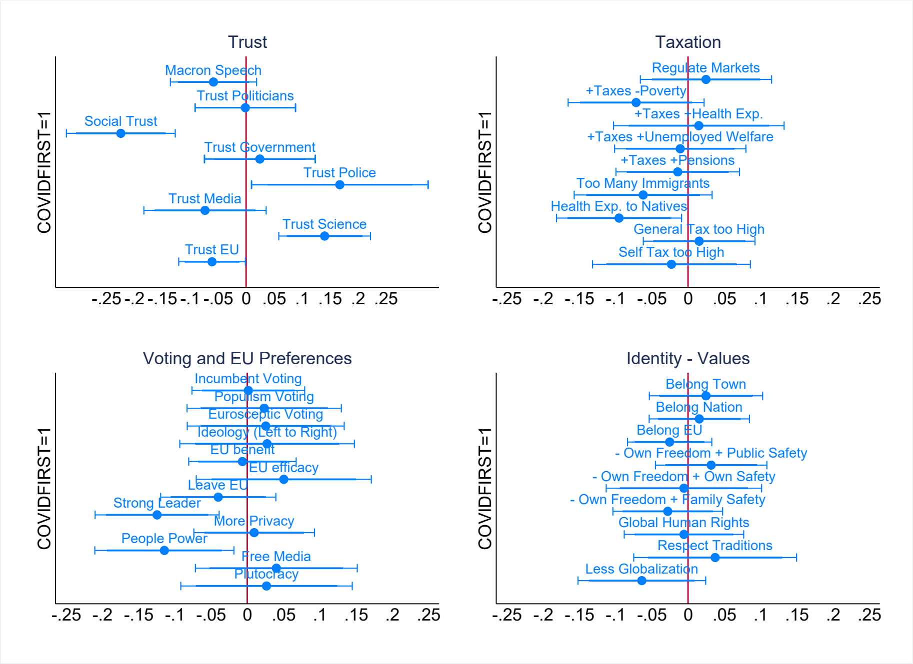
Figure A3: Effect of the intervention in the Netherlands



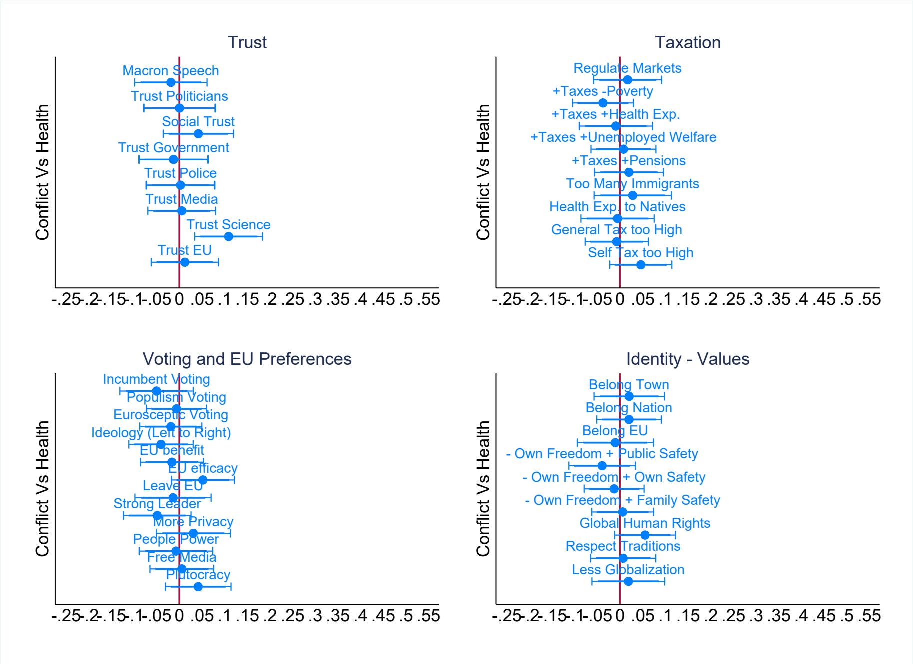
The figure shows the impact of COVIDFIRST on the four set of socio-political outcomes in the Netherlands. For each coefficient, 95% (delimited by horizontal bars) and 90% (bold line) confidence intervals are shown.

Figure A4: Effect of the intervention in Spain



The figure shows the impact of COVIDFIRST on the four set of socio-political outcomes in Spain. For each coefficient, 95% (delimited by horizontal bars) and 90% (bold line) confidence intervals are shown.

Figure A5: Effect of the Conflict condition in Germany, Italy and the Netherlands



The figure shows the impact of the Conflict condition compared to the Health condition (COVID-19 health treatment) on the four set of socio-political outcomes among respondents in Germany, Italy and the Netherlands. For each coefficient, 95% (delimited by horizontal bars) and 90% (bold line) confidence intervals are shown.

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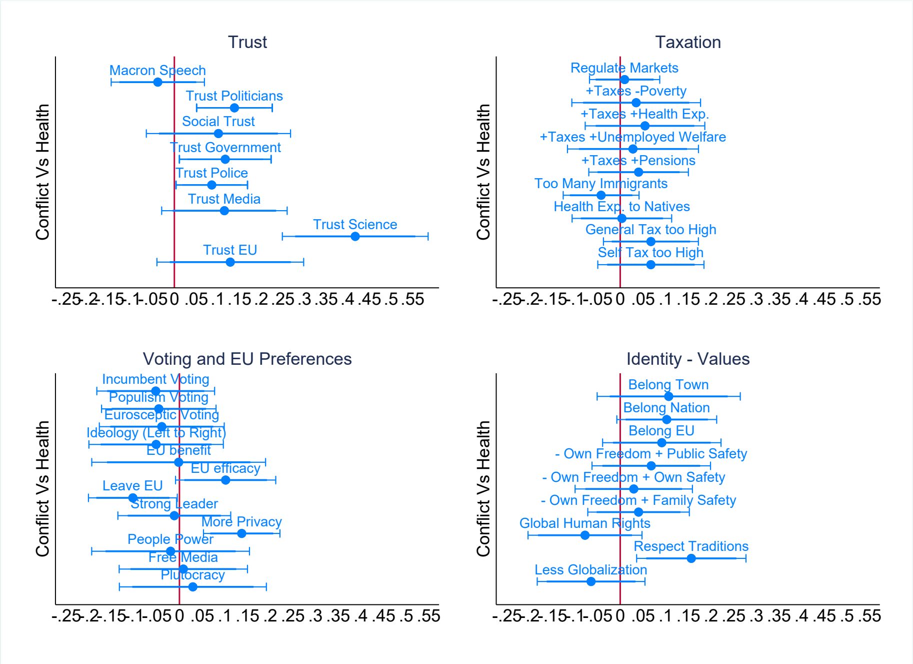
Figure A6: Effect of the Conflict condition in Spain



The figure shows the impact of the Conflict condition compared to the Health condition (COVID-19 health treatment) on the four set of socio-political outcomes among Spanish respondents. For each coefficient, 95% (delimited by horizontal bars) and 90% (bold line) confidence intervals are shown.

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B Tables

B.1 Pooled analyses: COVIDFIRST vs Baseline

Table B1: Effects of Covidfirst vs Baseline - Trust outcomes

	Macron Speech	Trust Politicians	Social Trust	Trust Government	Trust Police	Trust Media	Trust Science	Trust EU
Covidfirst	-0.143***	-0.0389**	-0.128***	0.00441	0.0817***	-0.0842***	0.0886***	-0.120***
	(0.0199)	(0.0195)	(0.0282)	(0.0229)	(0.0272)	(0.0210)	(0.0211)	(0.0199)
Observations	8,235	8,235	8,235	8,235	8,235	8,235	8,235	8,235
R-squared	0.063	0.183	0.063	0.119	0.034	0.144	0.046	0.027

The table presents estimates from OLS models. The outcome variables are stated in the first row. The sample compares the COVIDFIRST condition to the Baseline group. Controls include gender, age groups, employment status, education, immigrant status, family status and number of family members, equivalised household income (coded into five quantiles), a dummy to define the position of the Macron Speech question (see Section 3.1 for more details) and country fixed effects. All controls are omitted to enhance readability. Robust standard errors clustered at the province level are in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table B2: Effects of Covidfirst vs Baseline - Taxation outcomes

	Regulate Markets	+Taxes -Poverty	+Taxes +Health Exp.	+Taxes +Unemp. Welf.	+Taxes +Pensions	Too Many Immigrants	Health Exp. to Natives	General Tax too High	Self Tax too High
Covidfirst	-0.0269	-0.0974***	-0.0705***	-0.0578***	-0.0707***	-0.0138	-0.0653***	0.0297	0.0581*
	(0.0232)	(0.0219)	(0.0204)	(0.0210)	(0.0187)	(0.0253)	(0.0205)	(0.0200)	(0.0296)
Observations	8,235	8,235	8,235	8,235	8,235	8,235	8,235	8,235	8,235
R-squared	0.072	0.016	0.052	0.054	0.046	0.027	0.019	0.124	0.106

The table presents estimates from OLS models. The outcome variables are stated in the first row. The sample compares the COVIDFIRST condition to the Baseline group. Controls include gender, age groups, employment status, education, immigrant status, family status and number of family members, equivalised household income (coded into five quantiles), a dummy to define the position of the Macron Speech question (see Section 3.1 for more details) and country fixed effects. All controls are omitted to enhance readability. Robust standard errors clustered at the province level are in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table B3: Effects of Covidfirst vs Baseline - Voting outcomes

	Incumbent Voting	Populism Voting	Euroscept. Voting	Ideology Left/right	EU benefit	EU efficacy	Leave EU	Strong Leader	More Privacy	People Power	Free Media	Plutocra.
Covidfirst	0.0183	-0.0154	-0.00823	0.0339	-0.103***	-0.0983***	0.0134	-0.0545**	-0.0376*	-0.0515**	-0.000363	-0.000523
	(0.0216)	(0.0220)	(0.0223)	(0.0236)	(0.0216)	(0.0243)	(0.0227)	(0.0259)	(0.0223)	(0.0235)	(0.0239)	(0.0236)
Observations	8,235	8,235	8,235	8,235	8,235	8,235	8,235	8,235	8,235	8,235	8,235	8,235
R-squared	0.015	0.083	0.064	0.053	0.069	0.058	0.042	0.026	0.037	0.041	0.078	0.045

The table presents estimates from OLS models. The outcome variables are stated in the first row. The sample compares the COVIDFIRST condition to the Baseline group. Controls include gender, age groups, employment status, education, immigrant status, family status and number of family members, equivalised household income (coded into five quantiles), a dummy to define the position of the Macron Speech question (see Section 3.1 for more details) and country fixed effects. All controls are omitted to enhance readability. Robust standard errors clustered at the province level are in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table B4: Effects of Covidfirst vs Baseline - Identity outcomes

	Belong Town	Belong Nation	Belong EU	- Own Freedom + Public Safety	- Own Freedom + Own Safety	- Own Freedom + Family Safety	Global Human Rights	Respect Traditions	Less Globalization
Covidfirst	-0.0151	0.0263	-0.0763***	-0.0182	-0.00709	-0.0211	0.00470	0.0104	-0.00287
	(0.0241)	(0.0229)	(0.0196)	(0.0226)	(0.0212)	(0.0216)	(0.0234)	(0.0238)	(0.0231)
Observations	8,235	8,235	8,235	8,235	8,235	8,235	8,235	8,235	8,235
R-squared	0.030	0.028	0.037	0.010	0.016	0.026	0.031	0.052	0.049

The table presents estimates from OLS models. The outcome variables are stated in the first row. The sample compares the COVIDFIRST condition to the Baseline group. Controls include gender, age groups, employment status, education, immigrant status, family status and number of family members, equivalised household income (coded into five quantiles), a dummy to define the position of the Macron Speech question (see Section 3.1 for more details) and country fixed effects. All controls are omitted to enhance readability. Robust standard errors clustered at the province level are in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

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B.2 Condition comparisons

B.2.1 Health vs Baseline

Table B5: Effects of Health vs the Baseline: Trust outcomes

	Macron Speech	Trust Politicians	Social Trust	Trust Government	Trust Police	Trust Media	Trust Science	Trust EU
Health	-0.116***	-0.0304	-0.129***	0.0185	0.0896***	-0.0753**	0.0375	-0.110***
	(0.0284)	(0.0282)	(0.0330)	(0.0298)	(0.0328)	(0.0298)	(0.0314)	(0.0281)
Observations	4,571	4,571	4,571	4,571	4,571	4,571	4,571	4,571
R-squared	0.063	0.184	0.064	0.120	0.034	0.145	0.052	0.029

The table presents estimates from OLS models. The outcome variables are stated in the first row. The sample compares the Health condition to the Baseline group. Controls include gender, age groups, employment status, education, immigrant status, family status and number of family members, equivalised household income (coded into five quantiles), a dummy to define the position of the Macron Speech question (see Section 3.1 for more details) and country fixed effects. All controls are omitted to enhance readability. Robust standard errors clustered at the province level are in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table B6: Effects of Health vs the Baseline: Taxation outcomes

	Regulate Markets	+Taxes -Poverty	+Taxes +Health Exp.	+Taxes +Unemp. Welf.	+Taxes +Pensions	Too Many Immigrants	Health Exp. to Natives	General Tax too High	Self Tax too High
Health	-0.0213	-0.0834***	-0.0536	-0.0583**	-0.0839***	-0.0151	-0.0668**	0.00415	0.0153
	(0.0312)	(0.0283)	(0.0335)	(0.0289)	(0.0295)	(0.0309)	(0.0289)	(0.0238)	(0.0291)
Observations	4,571	4,571	4,571	4,571	4,571	4,571	4,571	4,571	4,571
R-squared	0.073	0.016	0.052	0.055	0.046	0.027	0.019	0.125	0.106

The table presents estimates from OLS models. The outcome variables are stated in the first row. The sample compares the Health condition to the Baseline group. Controls include gender, age groups, employment status, education, immigrant status, family status and number of family members, equivalised household income (coded into five quantiles), a dummy to define the position of the Macron Speech question (see Section 3.1 for more details) and country fixed effects. All controls are omitted to enhance readability. Robust standard errors clustered at the province level are in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table B7: Effects of Health vs the Baseline: Voting outcomes

	Incumbent Voting	Populism Voting	Euroscept. Voting	Ideology Left/right	EU benefit	EU efficacy	Leave EU	Strong Leader	More Privacy	People Power	Free Media	Plutocra.
Health	0.0631**	0.00903	0.0193	0.0504*	-0.0595**	-0.0969***	-0.00613	-0.0206	-0.0484	-0.0590	-0.0190	-0.0277
	(0.0287)	(0.0298)	(0.0312)	(0.0297)	(0.0290)	(0.0296)	(0.0304)	(0.0326)	(0.0313)	(0.0386)	(0.0304)	(0.0307)
Observations	4,571	4,571	4,571	4,571	4,571	4,571	4,571	4,571	4,571	4,571	4,571	4,571
R-squared	0.016	0.084	0.064	0.053	0.071	0.060	0.044	0.027	0.038	0.041	0.078	0.045

The table presents estimates from OLS models. The outcome variables are stated in the first row. The sample compares the Health condition to the Baseline group. Controls include gender, age groups, employment status, education, immigrant status, family status and number of family members, equivalised household income (coded into five quantiles), a dummy to define the position of the Macron Speech question (see Section 3.1 for more details) and country fixed effects. All controls are omitted to enhance readability. Robust standard errors clustered at the province level are in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table B8: Effects of Health vs the Baseline: Identity outcomes

	Belong Town	Belong Nation	Belong EU	- Own Freedom + Public Safety	- Own Freedom + Own Safety	- Own Freedom + Family Safety	Global Human Rights	Respect Traditions	Less Globalization
Health	-0.0334	0.0237	-0.0614**	0.0125	0.0155	-0.00508	0.00198	-0.0102	-0.00638
	(0.0282)	(0.0296)	(0.0289)	(0.0303)	(0.0297)	(0.0291)	(0.0312)	(0.0302)	(0.0288)
Observations	4,571	4,571	4,571	4,571	4,571	4,571	4,571	4,571	4,571
R-squared	0.030	0.029	0.037	0.011	0.017	0.027	0.031	0.052	0.049

The table presents estimates from OLS models. The outcome variables are stated in the first row. The sample compares the Health condition to the Baseline group. Controls include gender, age groups, employment status, education, immigrant status, family status and number of family members, equivalised household income (coded into five quantiles), a dummy to define the position of the Macron Speech question (see Section 3.1 for more details) and country fixed effects. All controls are omitted to enhance readability. Robust standard errors clustered at the province level are in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

B.2.2 Economic vs Health

Table B9: Effects of Economic vs Health: Trust outcomes

	Macron Speech	Trust Politicians	Social Trust	Trust Government	Trust Police	Trust Media	Trust Science	Trust EU
Economic	-0.174***	-0.0905***	-0.186***	-0.0438	0.0415	-0.134***	0.00536	-0.181***
	(0.0293)	(0.0273)	(0.0336)	(0.0289)	(0.0338)	(0.0273)	(0.0282)	(0.0293)
Observations	3,665	3,665	3,665	3,665	3,665	3,665	3,665	3,665
R-squared	0.063	0.184	0.064	0.120	0.034	0.145	0.052	0.029

The table presents estimates from OLS models. The outcome variables are stated in the first row. The sample compares the Economic condition to the Health group. Controls include gender, age groups, employment status, education, immigrant status, family status and number of family members, equivalised household income (coded into five quantiles), a dummy to define the position of the Macron Speech question (see Section 3.1 for more details) and country fixed effects. All controls are omitted to enhance readability. Robust standard errors clustered at the province level are in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table B10: Effects of Economic vs Health: Taxation outcomes

	Regulate Markets	+Taxes -Poverty	+Taxes +Health Exp.	+Taxes +Unemp. Welf.	+Taxes +Pensions	Too Many Immigrants	Health Exp. to Natives	General Tax too High	Self Tax too High
Economic	-0.0556*	-0.106***	-0.110***	-0.0716**	-0.0685**	-0.0246	-0.0615**	0.0706**	0.0911**
	(0.0298)	(0.0308)	(0.0291)	(0.0281)	(0.0277)	(0.0316)	(0.0284)	(0.0298)	(0.0374)
Observations	3,665	3,665	3,665	3,665	3,665	3,665	3,665	3,665	3,665
R-squared	0.073	0.016	0.052	0.055	0.046	0.027	0.019	0.125	0.106

The table presents estimates from OLS models. The outcome variables are stated in the first row. The sample compares the Economic condition to the Health group. Controls include gender, age groups, employment status, education, immigrant status, family status and number of family members, equivalised household income (coded into five quantiles), a dummy to define the position of the Macron Speech question (see Section 3.1 for more details) and country fixed effects. All controls are omitted to enhance readability. Robust standard errors clustered at the province level are in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

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Table B11: Effects of Economic vs Health: Voting outcomes

	Incumbent Voting	Populism Voting	Euroscept. Voting	Ideology Left/right	EU benefit	EU efficacy	Leave EU	Strong Leader	More Privacy	People Power	Free Media	Plutocra.
Economic	-0.0210	-0.0449	-0.0354	0.0449	-0.176***	-0.166***	0.0862***	-0.0838**	-0.0740**	-0.0255	0.0311	0.0154
	(0.0300)	(0.0287)	(0.0286)	(0.0361)	(0.0332)	(0.0343)	(0.0287)	(0.0355)	(0.0309)	(0.0283)	(0.0297)	(0.0294)
Observations	3,665	3,665	3,665	3,665	3,665	3,665	3,665	3,665	3,665	3,665	3,665	3,665
R-squared	0.016	0.084	0.064	0.053	0.071	0.060	0.044	0.027	0.038	0.041	0.078	0.045

The table presents estimates from OLS models. The outcome variables are stated in the first row. The sample compares the Economic condition to the Health group. Controls include gender, age groups, employment status, education, immigrant status, family status and number of family members, equivalised household income (coded into five quantiles), a dummy to define the position of the Macron Speech question (see Section 3.1 for more details) and country fixed effects. All controls are omitted to enhance readability. Robust standard errors clustered at the province level are in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table B12: Effects of Economic vs Health: Identity outcomes

	Belong Town	Belong Nation	Belong EU	- Own Freedom + Public Safety	- Own Freedom + Own Safety	- Own Freedom + Family Safety	Global Human Rights	Respect Traditions	Less Globalization
Economic	-0.0216	-0.00615	-0.122***	-0.0689**	-0.0532*	-0.0706**	-0.0116	0.00920	0.00623
	(0.0332)	(0.0317)	(0.0279)	(0.0300)	(0.0281)	(0.0295)	(0.0290)	(0.0312)	(0.0287)
Observations	3,665	3,665	3,665	3,665	3,665	3,665	3,665	3,665	3,665
R-squared	0.030	0.029	0.037	0.011	0.017	0.027	0.031	0.052	0.049

The table presents estimates from OLS models. The outcome variables are stated in the first row. The sample compares the Economic condition to the Health group. Controls include gender, age groups, employment status, education, immigrant status, family status and number of family members, equivalised household income (coded into five quantiles), a dummy to define the position of the Macron Speech question (see Section 3.1 for more details) and country fixed effects. All controls are omitted to enhance readability. Robust standard errors clustered at the province level are in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

B.2.3 Conflict vs Health

Table B13: Effects of Conflict vs Health: Trust outcomes

	Macron Speech	Trust Politicians	Social Trust	Trust Government	Trust Police	Trust Media	Trust Science	Trust EU
Conflict	-0.139***	0.00445	-0.0697**	0.0386	0.114***	-0.0426	0.223***	-0.0682**
	(0.0296)	(0.0258)	(0.0317)	(0.0273)	(0.0316)	(0.0280)	(0.0387)	(0.0298)
Observations	3,663	3,663	3,663	3,663	3,663	3,663	3,663	3,663
R-squared	0.063	0.184	0.064	0.120	0.034	0.145	0.052	0.029

The table presents estimates from OLS models. The outcome variables are stated in the first row. The sample compares the Conflict condition to the Health group. Controls include gender, age groups, employment status, education, immigrant status, family status and number of family members, equivalised household income (coded into five quantiles), a dummy to define the position of the Macron Speech question (see Section 3.1 for more details) and country fixed effects. All controls are omitted to enhance readability. Robust standard errors clustered at the province level are in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

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Table B14: Effects of Conflict vs Health: Taxation outcomes

	Regulate Markets	+Taxes -Poverty	+Taxes +Health Exp.	+Taxes +Unemp. Welf.	+Taxes +Pensions	Too Many Immigrants	Health Exp. to Natives	General Tax too High	Self Tax too High
Conflict	-0.00380	-0.103***	-0.0478	-0.0436	-0.0597**	-0.00167	-0.0676**	0.0144	0.0679**
	(0.0267)	(0.0299)	(0.0310)	(0.0293)	(0.0295)	(0.0320)	(0.0304)	(0.0258)	(0.0284)
Observations	3,663	3,663	3,663	3,663	3,663	3,663	3,663	3,663	3,663
R-squared	0.073	0.016	0.052	0.055	0.046	0.027	0.019	0.125	0.106

The table presents estimates from OLS models. The outcome variables are stated in the first row. The sample compares the Conflict condition to the Health group. Controls include gender, age groups, employment status, education, immigrant status, family status and number of family members, equivalised household income (coded into five quantiles), a dummy to define the position of the Macron Speech question (see Section 3.1 for more details) and country fixed effects. All controls are omitted to enhance readability. Robust standard errors clustered at the province level are in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table B15: Effects of Conflict vs Health: Voting outcomes

	Incumbent Voting	Populism Voting	Euroscept. Voting	Ideology Left/right	EU benefit	EU efficacy	Leave EU	Strong Leader	More Privacy	People Power	Free Media	Plutocra.
Conflict	0.0130	-0.0103	-0.00855	0.00639	-0.0745***	-0.0320	-0.0401	-0.0589**	0.00962	-0.0700**	-0.0133	0.0106
	(0.0271)	(0.0255)	(0.0246)	(0.0268)	(0.0281)	(0.0283)	(0.0299)	(0.0298)	(0.0314)	(0.0304)	(0.0328)	(0.0285)
Observations	3,663	3,663	3,663	3,663	3,663	3,663	3,663	3,663	3,663	3,663	3,663	3,663
R-squared	0.016	0.084	0.064	0.053	0.071	0.060	0.044	0.027	0.038	0.041	0.078	0.045

The table presents estimates from OLS models. The outcome variables are stated in the first row. The sample compares the Conflict condition to the Health group. Controls include gender, age groups, employment status, education, immigrant status, family status and number of family members, equivalised household income (coded into five quantiles), a dummy to define the position of the Macron Speech question (see Section 3.1 for more details) and country fixed effects. All controls are omitted to enhance readability. Robust standard errors clustered at the province level are in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table B16: Effects of Conflict vs Health: Identity outcomes

	Belong Town	Belong Nation	Belong EU	- Own Freedom + Public Safety	- Own Freedom + Own Safety	- Own Freedom + Family Safety	Global Human Rights	Respect Traditions	Less Globalization
Conflict	0.00957	0.0616**	-0.0454	0.00197	0.0167	0.0127	0.0237	0.0323	-0.00851
	(0.0308)	(0.0260)	(0.0288)	(0.0292)	(0.0314)	(0.0294)	(0.0270)	(0.0290)	(0.0300)
Observations	3,663	3,663	3,663	3,663	3,663	3,663	3,663	3,663	3,663
R-squared	0.030	0.029	0.037	0.011	0.017	0.027	0.031	0.052	0.049

The table presents estimates from OLS models. The outcome variables are stated in the first row. The sample compares the Conflict condition to the Health group. Controls include gender, age groups, employment status, education, immigrant status, family status and number of family members, equivalised household income (coded into five quantiles), a dummy to define the position of the Macron Speech question (see Section 3.1 for more details) and country fixed effects. All controls are omitted to enhance readability. Robust standard errors clustered at the province level are in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

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B.3 Country analyses

B.3.1 Germany

Table B17: Effects of Covidfirst vs Baseline - Germany: Trust outcomes

	Macron Speech	Trust Politicians	Social Trust	Trust Government	Trust Police	Trust Media	Trust Science	Trust EU
Covidfirst	-0.166***	-0.0399	-0.0278	-0.0258	0.0482	-0.0690	0.170***	-0.156***
	(0.0447)	(0.0433)	(0.0463)	(0.0429)	(0.0471)	(0.0457)	(0.0479)	(0.0441)
Observations	2,161	2,161	2,161	2,161	2,161	2,161	2,161	2,161
R-squared	0.031	0.030	0.068	0.046	0.049	0.041	0.046	0.032

The table presents estimates from OLS models. The outcome variables are stated in the first row. The sample solely includes observations from Germany and compares the COVIDFIRST condition to the Baseline condition. Controls include gender, age groups, employment status, education, immigrant status, family status and number of family members, equivalised household income (coded into five quantiles) and a dummy to define the position of the Macron Speech question (see Section 3.1 for more details). All controls are omitted to enhance readability. Robust standard errors clustered at the province level are in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table B18: Effects of Covidfirst vs Baseline - Germany: Taxation outcomes

	Regulate Markets	+Taxes -Poverty	+Taxes +Health Exp.	+Taxes +Unemp. Welf.	+Taxes +Pensions	Too Many Immigrants	Health Exp. to Natives	General Tax too High	Self Tax too High
Covidfirst	-0.0913*	-0.0823*	-0.0669	-0.0582	-0.0725	-0.0302	-0.0424	-0.0305	0.0392
	(0.0481)	(0.0439)	(0.0507)	(0.0494)	(0.0481)	(0.0453)	(0.0426)	(0.0491)	(0.0485)
Observations	2,161	2,161	2,161	2,161	2,161	2,161	2,161	2,161	2,161
R-squared	0.007	0.021	0.010	0.023	0.009	0.034	0.028	0.020	0.015

The table presents estimates from OLS models. The outcome variables are stated in the first row. The sample solely includes observations from Germany and compares the COVIDFIRST condition to the Baseline condition. Controls include gender, age groups, employment status, education, immigrant status, family status and number of family members, equivalised household income (coded into five quantiles) and a dummy to define the position of the Macron Speech question (see Section 3.1 for more details). All controls are omitted to enhance readability. Robust standard errors clustered at the province level are in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table B19: Effects of Covidfirst vs Baseline - Germany: Voting outcomes

	Incumbent Voting	Populism Voting	Euroscept. Voting	Ideology Left/right	EU benefit	EU efficacy	Leave EU	Strong Leader	More Privacy	People Power	Free Media	Plutocra.
Covidfirst	-0.00493	0.00578	0.00584	0.0248	-0.125***	-0.180***	0.0626	-0.0957**	-0.0580	-0.0757*	-0.0393	-0.0511
	(0.0463)	(0.0347)	(0.0351)	(0.0326)	(0.0415)	(0.0403)	(0.0426)	(0.0400)	(0.0480)	(0.0426)	(0.0469)	(0.0450)
Observations	2,161	2,161	2,161	2,161	2,161	2,161	2,161	2,161	2,161	2,161	2,161	2,161
R-squared	0.026	0.009	0.009	0.017	0.055	0.027	0.020	0.018	0.025	0.033	0.030	0.019

The table presents estimates from OLS models. The outcome variables are stated in the first row. The sample solely includes observations from Germany and compares the COVIDFIRST condition to the Baseline condition. Controls include gender, age groups, employment status, education, immigrant status, family status and number of family members, equivalised household income (coded into five quantiles) and a dummy to define the position of the Macron Speech question (see Section 3.1 for more details). All controls are omitted to enhance readability. Robust standard errors clustered at the province level are in parentheses. $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table B20: Effects of Covidfirst vs Baseline - Germany: Identity outcomes

	Belong Town	Belong Nation	Belong EU	- Own Freedom + Public Safety	- Own Freedom + Own Safety	- Own Freedom + Family Safety	Global Human Rights	Respect Traditions	Less Globalization
Covidfirst	-0.0732	-0.00480	-0.157***	-0.0887*	-0.0299	-0.0778*	-0.0558	-0.0534	-0.00949
	(0.0503)	(0.0461)	(0.0461)	(0.0472)	(0.0472)	(0.0443)	(0.0568)	(0.0517)	(0.0450)
Observations	2,161	2,161	2,161	2,161	2,161	2,161	2,161	2,161	2,161
R-squared	0.027	0.033	0.040	0.005	0.010	0.024	0.019	0.014	0.007

The table presents estimates from OLS models. The outcome variables are stated in the first row. The sample solely includes observations from Germany and compares the COVIDFIRST condition to the Baseline condition. Controls include gender, age groups, employment status, education, immigrant status, family status and number of family members, equivalised household income (coded into five quantiles) and a dummy to define the position of the Macron Speech question (see Section 3.1 for more details). All controls are omitted to enhance readability. Robust standard errors clustered at the province level are in parentheses.
* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

B.3.2 Italy

Table B21: Effects of Covidfirst vs Baseline - Italy: Trust outcomes

	Macron Speech	Trust Politicians	Social Trust	Trust Government	Trust Police	Trust Media	Trust Science	Trust EU
Covidfirst	-0.167***	-0.0834*	-0.110**	-0.00220	0.0781*	-0.124***	0.0213	-0.152***
	(0.0410)	(0.0427)	(0.0515)	(0.0455)	(0.0429)	(0.0425)	(0.0535)	(0.0463)
Observations	2,003	2,003	2,003	2,003	2,003	2,003	2,003	2,003
R-squared	0.051	0.020	0.023	0.025	0.043	0.015	0.029	0.056

The table presents estimates from OLS models. The outcome variables are stated in the first row. The sample solely includes observations from Italy and compares the COVIDFIRST condition to the Baseline condition. Controls include gender, age groups, employment status, education, immigrant status, family status and number of family members, equivalised household income (coded into five quantiles) and a dummy to define the position of the Macron Speech question (see Section 3.1 for more details). All controls are omitted to enhance readability. Robust standard errors clustered at the province level are in parentheses.
$p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table B22: Effects of Covidfirst vs Baseline - Italy: Taxation outcomes

	Regulate Markets	+Taxes -Poverty	+Taxes +Health Exp.	+Taxes +Unemp. Welf.	+Taxes +Pensions	Too Many Immigrants	Health Exp. to Natives	General Tax too High	Self Tax too High
Covidfirst	-0.0209	-0.121**	-0.128***	-0.0730*	-0.110***	0.0275	-0.0998*	0.117***	0.168***
	(0.0436)	(0.0478)	(0.0432)	(0.0415)	(0.0385)	(0.0499)	(0.0513)	(0.0443)	(0.0445)
Observations	2,003	2,003	2,003	2,003	2,003	2,003	2,003	2,003	2,003
R-squared	0.011	0.027	0.037	0.032	0.033	0.034	0.027	0.015	0.022

The table presents estimates from OLS models. The outcome variables are stated in the first row. The sample solely includes observations from Italy and compares the COVIDFIRST condition to the Baseline condition. Controls include gender, age groups, employment status, education, immigrant status, family status and number of family members, equivalised household income (coded into five quantiles) and a dummy to define the position of the Macron Speech question (see Section 3.1 for more details). All controls are omitted to enhance readability. Robust standard errors clustered at the province level are in parentheses.
* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

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Table B23: Effects of Covidfirst vs Baseline - Italy: Voting outcomes

	Incumbent Voting	Populism Voting	Euroscept. Voting	Ideology Left/right	EU benefit	EU efficacy	Leave EU	Strong Leader	More Privacy	People Power	Free Media	Plutocra.
Covidfirst	0.0331	-0.0240	0.00307	0.0764	-0.113**	-0.111**	0.0374	0.00310	-0.0547	0.0417	0.0177	0.0339
	(0.0483)	(0.0581)	(0.0574)	(0.0508)	(0.0476)	(0.0440)	(0.0516)	(0.0643)	(0.0543)	(0.0571)	(0.0478)	(0.0517)
Observations	2,003	2,003	2,003	2,003	2,003	2,003	2,003	2,003	2,003	2,003	2,003	2,003
R-squared	0.031	0.023	0.021	0.019	0.063	0.042	0.036	0.026	0.015	0.036	0.027	0.013

The table presents estimates from OLS models. The outcome variables are stated in the first row. The sample solely includes observations from Italy and compares the COVIDFIRST condition to the Baseline condition. Controls include gender, age groups, employment status, education, immigrant status, family status and number of family members, equivalised household income (coded into five quantiles) and a dummy to define the position of the Macron Speech question (see Section 3.1 for more details). All controls are omitted to enhance readability. Robust standard errors clustered at the province level are in parentheses.
* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table B24: Effects of Covidfirst vs Baseline - Italy: Identity outcomes

	Belong Town	Belong Nation	Belong EU	- Own Freedom + Public Safety	- Own Freedom + Own Safety	- Own Freedom + Family Safety	Global Human Rights	Respect Traditions	Less Globalization
Covidfirst	-0.0121	0.0306	-0.0730	0.0230	0.0703	0.0814*	0.0309	-0.00787	0.0613
	(0.0534)	(0.0559)	(0.0488)	(0.0537)	(0.0457)	(0.0490)	(0.0470)	(0.0468)	(0.0497)
Observations	2,003	2,003	2,003	2,003	2,003	2,003	2,003	2,003	2,003
R-squared	0.026	0.031	0.056	0.013	0.012	0.030	0.014	0.048	0.026

The table presents estimates from OLS models. The outcome variables are stated in the first row. The sample solely includes observations from Italy and compares the COVIDFIRST condition to the Baseline condition. Controls include gender, age groups, employment status, education, immigrant status, family status and number of family members, equivalised household income (coded into five quantiles) and a dummy to define the position of the Macron Speech question (see Section 3.1 for more details). All controls are omitted to enhance readability. Robust standard errors clustered at the province level are in parentheses.
* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

B.3.3 The Netherlands

Table B25: Effects of Covidfirst vs Baseline - Netherlands: Trust outcomes

	Macron Speech	Trust Politicians	Social Trust	Trust Government	Trust Police	Trust Media	Trust Science	Trust EU
Covidfirst	-0.205***	-0.0319	-0.153**	0.0197	0.0403	-0.0799***	0.0147	-0.108**
	(0.0354)	(0.0254)	(0.0553)	(0.0373)	(0.0391)	(0.0223)	(0.0355)	(0.0369)
Observations	2,071	2,071	2,071	2,071	2,071	2,071	2,071	2,071
R-squared	0.055	0.022	0.023	0.027	0.033	0.019	0.020	0.027

The table presents estimates from OLS models. The outcome variables are stated in the first row. The sample solely includes observations from the Netherlands and compares the COVIDFIRST condition to the Baseline condition. Controls include gender, age groups, employment status, education, immigrant status, family status and number of family members, equivalised household income (coded into five quantiles) and a dummy to define the position of the Macron Speech question (see Section 3.1 for more details). All controls are omitted to enhance readability. Robust standard errors clustered at the province level are in parentheses.
* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table B26: Effects of Covidfirst vs Baseline - Netherlands: Taxation outcomes

	Regulate Markets	+Taxes -Poverty	+Taxes +Health Exp.	+Taxes +Unemp. Welf.	+Taxes +Pensions	Too Many Immigrants	Health Exp. to Natives	General Tax too High	Self Tax too High
Covidfirst	-0.00396	-0.109**	-0.0963***	-0.0738	-0.0926**	0.0151	-0.0259	0.0257	0.0519
	(0.0528)	(0.0468)	(0.0293)	(0.0429)	(0.0325)	(0.0457)	(0.0367)	(0.0270)	(0.0446)
Observations	2,071	2,071	2,071	2,071	2,071	2,071	2,071	2,071	2,071
R-squared	0.007	0.015	0.012	0.009	0.035	0.017	0.035	0.012	0.021

The table presents estimates from OLS models. The outcome variables are stated in the first row. The sample solely includes observations from the Netherlands and compares the COVIDFIRST condition to the Baseline condition. Controls include gender, age groups, employment status, education, immigrant status, family status and number of family members, equivalised household income (coded into five quantiles) and a dummy to define the position of the Macron Speech question (see Section 3.1 for more details). All controls are omitted to enhance readability. Robust standard errors clustered at the province level are in parentheses.
* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table B27: Effects of Covidfirst vs Baseline - Netherlands: Voting outcomes

	Incumbent Voting	Populism Voting	Euroscept. Voting	Ideology Left/right	EU benefit	EU efficacy	Leave EU	Strong Leader	More Privacy	People Power	Free Media	Plutocra.
Covidfirst	0.0421	-0.0682**	-0.0689**	0.00962	-0.161***	-0.156***	-0.0118	0.000585	-0.0301	-0.0483	-0.00686	-0.00161
	(0.0418)	(0.0308)	(0.0311)	(0.0546)	(0.0386)	(0.0384)	(0.0463)	(0.0434)	(0.0349)	(0.0360)	(0.0469)	(0.0275)
Observations	2,071	2,071	2,071	2,071	2,071	2,071	2,071	2,071	2,071	2,071	2,071	2,071
R-squared	0.034	0.010	0.010	0.048	0.015	0.018	0.029	0.013	0.029	0.022	0.051	0.019

The table presents estimates from OLS models. The outcome variables are stated in the first row. The sample solely includes observations from the Netherlands and compares the COVIDFIRST condition to the Baseline condition. Controls include gender, age groups, employment status, education, immigrant status, family status and number of family members, equivalised household income (coded into five quantiles) and a dummy to define the position of the Macron Speech question (see Section 3.1 for more details). All controls are omitted to enhance readability. Robust standard errors clustered at the province level are in parentheses.
* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table B28: Effects of Covidfirst vs Baseline - Netherlands: Identity outcomes

	Belong Town	Belong Nation	Belong EU	- Own Freedom + Public Safety	- Own Freedom + Own Safety	- Own Freedom + Family Safety	Global Human Rights	Respect Traditions	Less Globalization
Covidfirst	-0.00668	0.0677*	-0.0497*	-0.0349	-0.0631*	-0.0592	0.0296	0.0594	0.00482
	(0.0406)	(0.0375)	(0.0269)	(0.0335)	(0.0345)	(0.0462)	(0.0356)	(0.0362)	(0.0369)
Observations	2,071	2,071	2,071	2,071	2,071	2,071	2,071	2,071	2,071
R-squared	0.019	0.033	0.016	0.009	0.009	0.020	0.020	0.043	0.009

The table presents estimates from OLS models. The outcome variables are stated in the first row. The sample solely includes observations from the Netherlands and compares the COVIDFIRST condition to the Baseline condition. Controls include gender, age groups, employment status, education, immigrant status, family status and number of family members, equivalised household income (coded into five quantiles) and a dummy to define the position of the Macron Speech question (see Section 3.1 for more details). All controls are omitted to enhance readability. Robust standard errors clustered at the province level are in parentheses.
* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

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B.3.4 Spain

Table B29: Effects of Covidfirst vs Baseline - Spain: Trust outcomes

	Macron Speech	Trust Politicians	Social Trust	Trust Government	Trust Police	Trust Media	Trust Science	Trust EU
Covidfirst	-0.0583	-0.00136	-0.224***	0.0246	0.168**	-0.0735	0.141***	-0.0609**
	(0.0370)	(0.0429)	(0.0472)	(0.0472)	(0.0749)	(0.0524)	(0.0392)	(0.0284)
Observations	2,000	2,000	2,000	2,000	2,000	2,000	2,000	2,000
R-squared	0.041	0.010	0.044	0.008	0.019	0.005	0.024	0.021

The table presents estimates from OLS models. The outcome variables are stated in the first row. The sample solely includes observations from Spain and compares the COVIDFIRST condition to the Baseline condition. Controls include gender, age groups, employment status, education, immigrant status, family status and number of family members, equivalised household income (coded into five quantiles) and a dummy to define the position of the Macron Speech question (see Section 3.1 for more details). All controls are omitted to enhance readability. Robust standard errors clustered at the province level are in parentheses.
$p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table B30: Effects of Covidfirst vs Baseline - Spain: Taxation outcomes

	Regulate Markets	+Taxes -Poverty	+Taxes +Health Exp.	+Taxes +Unemp. Welf.	+Taxes +Pensions	Too Many Immigrants	Health Exp. to Natives	General Tax too High	Self Tax too High
Covidfirst	0.0247	-0.0718	0.0150	-0.0107	-0.0142	-0.0621	-0.0954**	0.0153	-0.0228
	(0.0419)	(0.0444)	(0.0561)	(0.0430)	(0.0407)	(0.0457)	(0.0414)	(0.0364)	(0.0519)
Observations	2,000	2,000	2,000	2,000	2,000	2,000	2,000	2,000	2,000
R-squared	0.027	0.010	0.009	0.005	0.011	0.037	0.042	0.013	0.018

The table presents estimates from OLS models. The outcome variables are stated in the first row. The sample solely includes observations from Spain and compares the COVIDFIRST condition to the Baseline condition. Controls include gender, age groups, employment status, education, immigrant status, family status and number of family members, equivalised household income (coded into five quantiles) and a dummy to define the position of the Macron Speech question (see Section 3.1 for more details). All controls are omitted to enhance readability. Robust standard errors clustered at the province level are in parentheses.
$p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table B31: Effects of Covidfirst vs Baseline - Spain: Voting outcomes

	Incumbent Voting	Populism Voting	Euroscept. Voting	Ideology Left/right	EU benefit	EU efficacy	Leave EU	Strong Leader	More Privacy	People Power	Free Media	Plutocra.
Covidfirst	0.00148	0.0234	0.0255	0.0275	-0.00643	0.0507	-0.0401	-0.125***	0.00950	-0.115**	0.0403	0.0266
	(0.0370)	(0.0508)	(0.0517)	(0.0576)	(0.0358)	(0.0579)	(0.0382)	(0.0412)	(0.0399)	(0.0461)	(0.0533)	(0.0562)
Observations	2,000	2,000	2,000	2,000	2,000	2,000	2,000	2,000	2,000	2,000	2,000	2,000
R-squared	0.004	0.007	0.009	0.015	0.067	0.031	0.021	0.023	0.009	0.016	0.016	0.014

The table presents estimates from OLS models. The outcome variables are stated in the first row. The sample solely includes observations from Spain and compares the COVIDFIRST condition to the Baseline condition. Controls include gender, age groups, employment status, education, immigrant status, family status and number of family members, equivalised household income (coded into five quantiles) and a dummy to define the position of the Macron Speech question (see Section 3.1 for more details). All controls are omitted to enhance readability. Robust standard errors clustered at the province level are in parentheses.
$p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table B32: Effects of Covidfirst vs Baseline - Spain: Identity outcomes

	Belong Town	Belong Nation	Belong EU	- Own Freedom + Public Safety	- Own Freedom + Own Safety	- Own Freedom + Family Safety	Global Human Rights	Respect Traditions	Less Globalization
1.Covidfirst	0.0250	0.0158	-0.0252	0.0320	-0.00581	-0.0281	-0.00553	0.0375	-0.0641
	(0.0377)	(0.0329)	(0.0277)	(0.0367)	(0.0510)	(0.0359)	(0.0392)	(0.0535)	(0.0428)
Observations	2,000	2,000	2,000	2,000	2,000	2,000	2,000	2,000	2,000
R-squared	0.023	0.013	0.030	0.006	0.010	0.023	0.017	0.038	0.011

The table presents estimates from OLS models. The outcome variables are stated in the first row. The sample solely includes observations from Spain and compares the COVIDFIRST condition to the Baseline condition. Controls include gender, age groups, employment status, education, immigrant status, family status and number of family members, equivalised household income (coded into five quantiles) and a dummy to define the position of the Macron Speech question (see Section 3.1 for more details). All controls are omitted to enhance readability. Robust standard errors clustered at the province level are in parentheses.
$p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

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B.4 Heterogeneity analysis: perceptions of COVID-19

B.4.1 Exposure to the virus

Table B33: Heterogeneous effects of having contracted the virus: Trust

	Macron Speech	Trust Politicians	Social Trust	Trust Government	Trust Police	Trust Media	Trust Science	Trust EU
Covidfirst	-0.144***	-0.0397**	-0.130***	0.00387	0.0808***	-0.0849***	0.0883***	-0.121***
	(0.0208)	(0.0197)	(0.0269)	(0.0214)	(0.0276)	(0.0209)	(0.0229)	(0.0205)
Contracted	0.00897	0.00976	0.0387***	0.00625	0.0266	0.0112	-0.00142	0.0194
	(0.0186)	(0.0175)	(0.0137)	(0.0173)	(0.0175)	(0.0205)	(0.0244)	(0.0190)
Covidfirst*contracted	0.0341	0.0304	0.00160	0.0200	-0.0105	0.0172	0.0207	0.0189
	(0.0268)	(0.0206)	(0.0211)	(0.0194)	(0.0188)	(0.0259)	(0.0240)	(0.0212)
Observations	8,235	8,235	8,235	8,235	8,235	8,235	8,235	8,235
R-squared	0.064	0.184	0.064	0.119	0.034	0.145	0.046	0.028

The table presents estimates from OLS models. The outcome variables are stated in the first row. The analysis interacts COVID-FIRST with an indicator variable indicating whether the respondent (or someone in his/her circle) contracted the virus. Controls include gender, age groups, employment status, education, immigrant status, family status and number of family members, equivalised household income (coded into five quantiles), a dummy to define the position of the Macron Speech question (see Section 3.1 for more details) and country fixed effects. All controls are omitted to enhance readability. Robust standard errors clustered at the province level are in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table B34: Heterogeneous effects of having contracted the virus: Taxation

	Regulate Markets	+Taxes -Poverty	+Taxes +Health Exp.	+Taxes +Unemp. Welf.	+Taxes +Pensions	Too Many Immigrants	Health Exp. to Natives	General Tax too High	Self Tax too High
Covidfirst	-0.0259	-0.0987***	-0.0711***	-0.0583***	-0.0711***	-0.0137	-0.0653***	0.0292	0.0568**
	(0.0227)	(0.0228)	(0.0230)	(0.0222)	(0.0209)	(0.0235)	(0.0210)	(0.0199)	(0.0255)
Contracted	-0.0401**	0.0240	-0.00327	0.00854	0.00293	0.00847	0.00597	0.0253*	0.0478***
	(0.0202)	(0.0154)	(0.0173)	(0.0155)	(0.0165)	(0.0228)	(0.0225)	(0.0152)	(0.0180)
Covidfirst*contracted	0.0452**	0.0245	0.0470*	0.00953	0.0219	-0.0315	-0.0188	-0.0352*	-0.0443**
	(0.0215)	(0.0192)	(0.0270)	(0.0217)	(0.0218)	(0.0241)	(0.0242)	(0.0182)	(0.0224)
Observations	8,235	8,235	8,235	8,235	8,235	8,235	8,235	8,235	8,235
R-squared	0.073	0.017	0.053	0.055	0.046	0.027	0.019	0.125	0.106

The table presents estimates from OLS models. The outcome variables are stated in the first row. The analysis interacts COVID-FIRST with an indicator variable indicating whether the respondent (or someone in his/her circle) contracted the virus. Controls include gender, age groups, employment status, education, immigrant status, family status and number of family members, equivalised household income (coded into five quantiles), a dummy to define the position of the Macron Speech question (see Section 3.1 for more details) and country fixed effects. All controls are omitted to enhance readability. Robust standard errors clustered at the province level are in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table B35: Heterogeneous effects of having contracted the virus: Voting

	Incumbent Voting	Populism Voting	Euroscept. Voting	Ideology Left/right	EU benefit	EU efficacy	Leave EU	Strong Leader	More Privacy	People Power	Free Media	Plutocra.
Covidfirst	0.0190	-0.0164	-0.00917	0.0328	-0.105***	-0.0999***	0.0135	-0.0547**	-0.0371*	-0.0514**	-0.000421	-0.000965
	(0.0214)	(0.0220)	(0.0222)	(0.0232)	(0.0212)	(0.0241)	(0.0225)	(0.0257)	(0.0222)	(0.0235)	(0.0240)	(0.0236)
Contracted	-0.0305*	0.0199	0.0227	0.0389*	0.0262	0.0213	0.00863	0.0136	-0.0200	0.0107	-0.00937	0.0127
	(0.0183)	(0.0201)	(0.0201)	(0.0207)	(0.0166)	(0.0182)	(0.0181)	(0.0196)	(0.0229)	(0.0162)	(0.0181)	(0.0178)
Covidfirst*contracted	0.0411*	0.00725	0.000967	-0.0346	0.0202	0.0507**	-0.0310	-0.0230	0.0191	-0.0348*	0.0319	-0.00546
	(0.0226)	(0.0209)	(0.0210)	(0.0222)	(0.0209)	(0.0242)	(0.0214)	(0.0227)	(0.0264)	(0.0209)	(0.0246)	(0.0207)
Observations	8,235	8,235	8,235	8,235	8,235	8,235	8,235	8,235	8,235	8,235	8,235	8,235
R-squared	0.015	0.084	0.064	0.054	0.070	0.061	0.042	0.026	0.037	0.041	0.078	0.045

The table presents estimates from OLS models. The outcome variables are stated in the first row. The analysis interacts COVID-FIRST with an indicator variable indicating whether the respondent (or someone in his/her circle) contracted the virus. Controls include gender, age groups, employment status, education, immigrant status, family status and number of family members, equivalised household income (coded into five quantiles), a dummy to define the position of the Macron Speech question (see Section 3.1 for more details) and country fixed effects. All controls are omitted to enhance readability. Robust standard errors clustered at the province level are in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table B36: Heterogeneous effects of having contracted the virus: Identity

	Belong Town	Belong Nation	Belong EU	- Own Freedom + Public Safety	- Own Freedom + Own Safety	- Own Freedom + Family Safety	Global Human Rights	Respect Traditions	Less Globalization
Covidfirst	-0.0154	0.0256	-0.0771***	-0.0196	-0.00777	-0.0218	0.00440	0.00994	-0.00300
	(0.0234)	(0.0227)	(0.0199)	(0.0225)	(0.0236)	(0.0236)	(0.0229)	(0.0239)	(0.0222)
Contracted	0.000460	0.0159	0.0118	0.0379**	0.0149	0.0235	0.00480	0.0153	0.00624
	(0.0198)	(0.0226)	(0.0183)	(0.0157)	(0.0192)	(0.0211)	(0.0162)	(0.0131)	(0.0179)
Covidfirst*contracted	0.0186	0.00500	0.0232	-0.00924	0.00525	-0.0189	0.00751	-0.00900	-0.00904
	(0.0210)	(0.0209)	(0.0208)	(0.0182)	(0.0240)	(0.0215)	(0.0211)	(0.0156)	(0.0245)
Observations	8,235	8,235	8,235	8,235	8,235	8,235	8,235	8,235	8,235
R-squared	0.030	0.029	0.038	0.011	0.016	0.026	0.031	0.052	0.049

The table presents estimates from OLS models. The outcome variables are stated in the first row. The analysis interacts COVID-FIRST with an indicator variable indicating whether the respondent (or someone in his/her circle) contracted the virus. Controls include gender, age groups, employment status, education, immigrant status, family status and number of family members, equivalised household income (coded into five quantiles), a dummy to define the position of the Macron Speech question (see Section 3.1 for more details) and country fixed effects. All controls are omitted to enhance readability. Robust standard errors clustered at the province level are in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

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B.4.2 Compliance with anti-diffusion measures

Table B37: Heterogeneous effects of compliance with anti-diffusion measures: Trust

	Macron Speech	Trust Politicians	Social Trust	Trust Government	Trust Police	Trust Media	Trust Science	Trust EU
Covidfirst	-0.143***	-0.0370*	-0.129***	0.00709	0.0846***	-0.0816***	0.0921***	-0.118***
	(0.0209)	(0.0193)	(0.0271)	(0.0208)	(0.0260)	(0.0202)	(0.0231)	(0.0205)
Obedience	0.0130	0.125***	-0.00675	0.182***	0.198***	0.176***	0.237***	0.136***
	(0.0198)	(0.0200)	(0.0203)	(0.0167)	(0.0192)	(0.0206)	(0.0215)	(0.0213)
Covidfirst*obedience	0.0403*	0.0478**	-0.0582**	0.0568***	-0.0147	0.0327	0.0797***	0.0192
	(0.0224)	(0.0220)	(0.0250)	(0.0208)	(0.0233)	(0.0233)	(0.0288)	(0.0260)
Observations	8,235	8,235	8,235	8,235	8,235	8,235	8,235	8,235
R-squared	0.065	0.206	0.065	0.161	0.066	0.179	0.118	0.047

The table presents estimates from OLS models. The outcome variables are stated in the first row. The analysis interacts COVID-FIRST with a variable indicating the respondent's level of compliance with anti-diffusion measures. Controls include gender, age groups, employment status, education, immigrant status, family status and number of family members, equivalised household income (coded into five quantiles), a dummy to define the position of the Macron Speech question (see Section 3.1 for more details) and country fixed effects. All controls are omitted to enhance readability. Robust standard errors clustered at the province level are in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table B38: Heterogeneous effects of compliance with anti-diffusion measures: Taxation

	Regulate Markets	+Taxes -Poverty	+Taxes +Health Exp.	+Taxes +Unemp. Welf.	+Taxes +Pensions	Too Many Immigrants	Health Exp. to Natives	General Tax too High	Self Tax too High
Covidfirst	-0.0254	-0.0957***	-0.0677***	-0.0558**	-0.0682***	-0.0142	-0.0668***	0.0293	0.0578**
	(0.0234)	(0.0227)	(0.0245)	(0.0225)	(0.0220)	(0.0235)	(0.0208)	(0.0200)	(0.0261)
Obedience	0.110***	0.117***	0.192***	0.142***	0.175***	-0.0244	-0.1000***	-0.0257	-0.0186
	(0.0215)	(0.0221)	(0.0212)	(0.0230)	(0.0214)	(0.0205)	(0.0215)	(0.0194)	(0.0214)
Covidfirst*obedience	-0.0165	0.0281	-0.00315	0.00661	-0.0223	-0.0298	-0.0247	-0.0448**	-0.0446*
	(0.0266)	(0.0255)	(0.0235)	(0.0275)	(0.0244)	(0.0251)	(0.0252)	(0.0223)	(0.0240)
Observations	8,235	8,235	8,235	8,235	8,235	8,235	8,235	8,235	8,235
R-squared	0.081	0.031	0.082	0.073	0.068	0.029	0.032	0.128	0.108

The table presents estimates from OLS models. The outcome variables are stated in the first row. The analysis interacts COVID-FIRST with a variable indicating the respondent's level of compliance with anti-diffusion measures. Controls include gender, age groups, employment status, education, immigrant status, family status and number of family members, equivalised household income (coded into five quantiles), a dummy to define the position of the Macron Speech question (see Section 3.1 for more details) and country fixed effects. All controls are omitted to enhance readability. Robust standard errors clustered at the province level are in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

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Table B39: Heterogeneous effects of compliance with anti-diffusion measures: Voting

	Incumbent Voting	Populism Voting	Euroscept. Voting	Ideology Left/right	EU benefit	EU efficacy	Leave EU	Strong Leader	More Privacy	People Power	Free Media	Plutocra.
Covidfirst	0.0203	-0.0157	-0.00867	0.0324	-0.101***	-0.0971***	0.0117	-0.0553**	-0.0394*	-0.0530**	0.000102	-0.000918
	(0.0214)	(0.0222)	(0.0225)	(0.0239)	(0.0213)	(0.0237)	(0.0221)	(0.0262)	(0.0218)	(0.0229)	(0.0242)	(0.0235)
Obedience	0.136***	-0.0202	-0.0293	-0.107***	0.132***	0.0849***	-0.118***	-0.0605**	-0.119***	-0.103***	0.0331	-0.0258
	(0.0164)	(0.0179)	(0.0183)	(0.0206)	(0.0213)	(0.0225)	(0.0243)	(0.0235)	(0.0202)	(0.0231)	(0.0229)	(0.0232)
Covidfirst*obedience	-0.00496	-0.0255	-0.0157	-0.0286	0.00845	0.0264	-0.00362	0.0136	0.0153	-0.0478**	-0.0322	-0.0387
	(0.0184)	(0.0220)	(0.0227)	(0.0241)	(0.0252)	(0.0262)	(0.0269)	(0.0281)	(0.0247)	(0.0233)	(0.0276)	(0.0288)
Observations	8,235	8,235	8,235	8,235	8,235	8,235	8,235	8,235	8,235	8,235	8,235	8,235
R-squared	0.031	0.085	0.065	0.068	0.086	0.067	0.056	0.029	0.047	0.058	0.078	0.048

The table presents estimates from OLS models. The outcome variables are stated in the first row. The analysis interacts COVIDFIRST with a variable indicating the respondent's level of compliance with anti-diffusion measures. Controls include gender, age groups, employment status, education, immigrant status, family status and number of family members, equivalised household income (coded into five quantiles), a dummy to define the position of the Macron Speech question (see Section 3.1 for more details) and country fixed effects. All controls are omitted to enhance readability. Robust standard errors clustered at the province level are in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table B40: Heterogeneous effects of compliance with anti-diffusion measures: Identity

	Belong Town	Belong Nation	Belong EU	- Own Freedom + Public Safety	- Own Freedom + Own Safety	- Own Freedom + Family Safety	Global Human Rights	Respect Traditions	Less Globalization
Covidfirst	-0.0129	0.0291	-0.0741***	-0.0149	-0.00395	-0.0176	0.00781	0.0120	-0.00318
	(0.0228)	(0.0214)	(0.0201)	(0.0217)	(0.0226)	(0.0232)	(0.0238)	(0.0236)	(0.0223)
Obedience	0.156***	0.187***	0.151***	0.227***	0.215***	0.239***	0.215***	0.107***	-0.0197
	(0.0228)	(0.0233)	(0.0209)	(0.0211)	(0.0228)	(0.0213)	(0.0274)	(0.0216)	(0.0220)
Covidfirst*obedience	-0.0487*	-0.0237	0.00103	-0.0167	-0.000168	-0.0101	-0.0274	-0.0349	-0.0276
	(0.0268)	(0.0262)	(0.0253)	(0.0264)	(0.0261)	(0.0244)	(0.0299)	(0.0239)	(0.0259)
Observations	8,235	8,235	8,235	8,235	8,235	8,235	8,235	8,235	8,235
R-squared	0.044	0.055	0.058	0.052	0.058	0.074	0.067	0.059	0.051

The table presents estimates from OLS models. The outcome variables are stated in the first row. The analysis interacts COVIDFIRST with a variable indicating the respondent's level of compliance with anti-diffusion measures. Controls include gender, age groups, employment status, education, immigrant status, family status and number of family members, equivalised household income (coded into five quantiles), a dummy to define the position of the Macron Speech question (see Section 3.1 for more details) and country fixed effects. All controls are omitted to enhance readability. Robust standard errors clustered at the province level are in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

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B.4.3 Worried about own health due to COVID-19

Table B41: Heterogeneous effects of concern with the epidemic: Trust

	Macron Speech	Trust Politicians	Social Trust	Trust Government	Trust Police	Trust Media	Trust Science	Trust EU
Covidfirst	-0.140***	-0.0332*	-0.126***	0.00909	0.0867***	-0.0786***	0.0931***	-0.114***
	(0.0212)	(0.0193)	(0.0272)	(0.0211)	(0.0268)	(0.0199)	(0.0225)	(0.0200)
Worried	0.0694***	0.113***	0.0578**	0.0908***	0.109***	0.113***	0.0945***	0.136***
	(0.0136)	(0.0199)	(0.0224)	(0.0223)	(0.0216)	(0.0207)	(0.0194)	(0.0209)
Covidfirst*worried	-0.0138	0.0317	-0.0422*	0.0371	-0.00224	0.0290	0.0137	-0.0107
	(0.0175)	(0.0227)	(0.0255)	(0.0240)	(0.0224)	(0.0215)	(0.0227)	(0.0264)
Observations	8,235	8,235	8,235	8,235	8,235	8,235	8,235	8,235
R-squared	0.066	0.199	0.064	0.130	0.044	0.160	0.055	0.043

The table presents estimates from OLS models. The outcome variables are stated in the first row. The analysis interacts COVID-FIRST with a variable indicating the respondent's level of concern with the epidemic. Controls include gender, age groups, employment status, education, immigrant status, family status and number of family members, equivalised household income (coded into five quantiles), a dummy to define the position of the Macron Speech question (see Section 3.1 for more details) and country fixed effects. All controls are omitted to enhance readability. Robust standard errors clustered at the province level are in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table B42: Heterogeneous effects of concern with the epidemic: Taxation

	Regulate Markets	+Taxes -Poverty	+Taxes +Health Exp.	+Taxes +Unemp. Welf.	+Taxes +Pensions	Too Many Immigrants	Health Exp. to Natives	General Tax too High	Self Tax too High
Covidfirst	-0.0221	-0.0937***	-0.0678***	-0.0537**	-0.0670***	-0.0120	-0.0596***	0.0306	0.0609**
	(0.0230)	(0.0231)	(0.0236)	(0.0227)	(0.0209)	(0.0234)	(0.0205)	(0.0198)	(0.0256)
Worried	0.0886***	0.0646***	0.0422**	0.0788***	0.0654***	0.0338*	0.130***	0.0211	0.0659***
	(0.0234)	(0.0197)	(0.0186)	(0.0230)	(0.0179)	(0.0205)	(0.0179)	(0.0188)	(0.0193)
Covidfirst*worried	0.0597**	0.0579**	0.0557**	0.0397	0.0561**	0.0169	-0.0208	-0.00984	-0.0222
	(0.0249)	(0.0240)	(0.0232)	(0.0246)	(0.0230)	(0.0236)	(0.0264)	(0.0206)	(0.0235)
Observations	8,235	8,235	8,235	8,235	8,235	8,235	8,235	8,235	8,235
R-squared	0.088	0.025	0.057	0.064	0.056	0.029	0.032	0.125	0.108

The table presents estimates from OLS models. The outcome variables are stated in the first row. The analysis interacts COVID-FIRST with a variable indicating the respondent's level of concern with the epidemic. Controls include gender, age groups, employment status, education, immigrant status, family status and number of family members, equivalised household income (coded into five quantiles), a dummy to define the position of the Macron Speech question (see Section 3.1 for more details) and country fixed effects. All controls are omitted to enhance readability. Robust standard errors clustered at the province level are in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table B43: Heterogeneous effects of concern with the epidemic: Voting

	Incumbent Voting	Populism Voting	Euroscept. Voting	Ideology Left/right	EU benefit	EU efficacy	Leave EU	Strong Leader	More Privacy	People Power	Free Media	Plutocra.
Covidfirst	0.0193	-0.0145	-0.00768	0.0371	-0.0989***	-0.0940***	0.0128	-0.0481*	-0.0340	-0.0480**	-0.00234	-0.00127
	(0.0216)	(0.0220)	(0.0223)	(0.0231)	(0.0216)	(0.0235)	(0.0226)	(0.0252)	(0.0224)	(0.0236)	(0.0236)	(0.0234)
Worried	0.0244	0.0113	0.00445	0.0706***	0.0970***	0.0891***	-0.0123	0.143***	0.0812***	0.0887***	-0.0478**	-0.0269
	(0.0208)	(0.0180)	(0.0177)	(0.0239)	(0.0210)	(0.0205)	(0.0193)	(0.0179)	(0.0237)	(0.0219)	(0.0187)	(0.0206)
Covidfirst*worried	-0.0118	0.0317	0.0260	-0.00892	0.00256	0.0182	0.00127	-0.0169	-0.0124	-0.0463*	0.0172	0.0373
	(0.0226)	(0.0231)	(0.0226)	(0.0302)	(0.0234)	(0.0242)	(0.0239)	(0.0243)	(0.0279)	(0.0239)	(0.0220)	(0.0243)
Observations	8,235	8,235	8,235	8,235	8,235	8,235	8,235	8,235	8,235	8,235	8,235	8,235
R-squared	0.015	0.085	0.064	0.057	0.078	0.067	0.042	0.042	0.042	0.045	0.079	0.045

The table presents estimates from OLS models. The outcome variables are stated in the first row. The analysis interacts COVID-FIRST with a variable indicating the respondent's level of concern with the epidemic. Controls include gender, age groups, employment status, education, immigrant status, family status and number of family members, equivalised household income (coded into five quantiles), a dummy to define the position of the Macron Speech question (see Section 3.1 for more details) and country fixed effects. All controls are omitted to enhance readability. Robust standard errors clustered at the province level are in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

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Table B44: Heterogeneous effects of concern with the epidemic: Identity

	Belong Town	Belong Nation	Belong EU	- Own Freedom + Public Safety	- Own Freedom + Own Safety	- Own Freedom + Family Safety	Global Human Rights	Respect Traditions	Less Globalization
Covidfirst	-0.0129	0.0306	-0.0715***	-0.00863	0.00184	-0.0141	0.00371	0.0139	0.00121
	(0.0232)	(0.0217)	(0.0199)	(0.0209)	(0.0230)	(0.0230)	(0.0230)	(0.0241)	(0.0220)
Worried	0.0412*	0.0888***	0.104***	0.202***	0.194***	0.144***	-0.0260	0.0726***	0.0899***
	(0.0212)	(0.0217)	(0.0184)	(0.0191)	(0.0198)	(0.0172)	(0.0191)	(0.0185)	(0.0201)
Covidfirst*worried	0.0271	0.0147	0.00452	0.0185	-0.000307	0.0262	0.0156	0.00713	-0.00439
	(0.0223)	(0.0237)	(0.0236)	(0.0237)	(0.0260)	(0.0272)	(0.0237)	(0.0227)	(0.0242)
Observations	8,235	8,235	8,235	8,235	8,235	8,235	8,235	8,235	8,235
R-squared	0.033	0.037	0.047	0.052	0.050	0.049	0.031	0.057	0.056

The table presents estimates from OLS models. The outcome variables are stated in the first row. The analysis interacts COVID-FIRST with a variable indicating the respondent's level of concern with the epidemic. Controls include gender, age groups, employment status, education, immigrant status, family status and number of family members, equivalised household income (coded into five quantiles), a dummy to define the position of the Macron Speech question (see Section 3.1 for more details) and country fixed effects. All controls are omitted to enhance readability. Robust standard errors clustered at the province level are in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

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B.5 Conflict condition: Spain vs other countries

Table B45: Effects of the Conflict condition in Germany, Italy and the Netherlands - Trust

	Macron Speech	Trust Politicians	Social Trust	Trust Government	Trust Police	Trust Media	Trust Science	Trust EU
Conflict	-0.0179	0.000863	0.0418	-0.0124	0.00262	0.00623	0.109***	0.0126
	(0.0409)	(0.0403)	(0.0397)	(0.0392)	(0.0385)	(0.0383)	(0.0383)	(0.0380)
Observations	2,782	2,782	2,782	2,782	2,782	2,782	2,782	2,782
R-squared	0.071	0.171	0.065	0.110	0.045	0.143	0.058	0.028

The table presents estimates from OLS models. The outcome variables are stated in the first row. The sample compares the Conflict condition to the Health group and it includes only respondents in Germany, Italy and the Netherlands. Controls include gender, age groups, employment status, education, immigrant status, family status and number of family members, equivalised household income (coded into five quantiles), a dummy to define the position of the Macron Speech question (see Section 3.1 for more details) and country fixed effects. All controls are omitted to enhance readability. Robust standard errors clustered at the province level are in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table B46: Effects of the Conflict condition in Germany, Italy and the Netherlands - Taxation

	Regulate Markets	+Taxes -Poverty	+Taxes +Health Exp.	+Taxes +Unemp. Welf.	+Taxes +Pensions	Too Many Immigrants	Health Exp. to Natives	General Tax too High	Self Tax too High
Conflict	0.0169	-0.0368	-0.00938	0.00789	0.0194	0.0270	-0.00505	-0.00851	0.0465
	(0.0383)	(0.0342)	(0.0413)	(0.0366)	(0.0388)	(0.0434)	(0.0413)	(0.0356)	(0.0349)
Observations	2,782	2,782	2,782	2,782	2,782	2,782	2,782	2,782	2,782
R-squared	0.076	0.011	0.035	0.044	0.028	0.025	0.018	0.147	0.093

The table presents estimates from OLS models. The outcome variables are stated in the first row. The sample compares the Conflict condition to the Health group and it includes only respondents in Germany, Italy and the Netherlands. Controls include gender, age groups, employment status, education, immigrant status, family status and number of family members, equivalised household income (coded into five quantiles), a dummy to define the position of the Macron Speech question (see Section 3.1 for more details) and country fixed effects. All controls are omitted to enhance readability. Robust standard errors clustered at the province level are in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table B47: Effects of the Conflict condition in Germany, Italy and the Netherlands - Voting

	Incumbent Voting	Populism Voting	Euroscept. Voting	Ideology Left/right	EU benefit	EU efficacy	Leave EU	Strong Leader	More Privacy	People Power	Free Media	Plutocra.
Conflict	-0.0512	-0.00623	-0.0188	-0.0410	-0.0163	0.0533	-0.0138	-0.0484	0.0314	-0.00661	0.00423	0.0428
	(0.0413)	(0.0337)	(0.0349)	(0.0363)	(0.0355)	(0.0354)	(0.0427)	(0.0381)	(0.0419)	(0.0412)	(0.0361)	(0.0366)
Observations	2,782	2,782	2,782	2,782	2,782	2,782	2,782	2,782	2,782	2,782	2,782	2,782
R-squared	0.024	0.105	0.083	0.045	0.069	0.056	0.036	0.032	0.038	0.045	0.073	0.054

The table presents estimates from OLS models. The outcome variables are stated in the first row. The sample compares the Conflict condition to the Health group and it includes only respondents in Germany, Italy and the Netherlands. Controls include gender, age groups, employment status, education, immigrant status, family status and number of family members, equivalised household income (coded into five quantiles), a dummy to define the position of the Macron Speech question (see Section 3.1 for more details) and country fixed effects. All controls are omitted to enhance readability. Robust standard errors clustered at the province level are in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table B48: Effects of the Conflict condition in Germany, Italy and the Netherlands - Identity

	Belong Town	Belong Nation	Belong EU	- Own Freedom + Public Safety	- Own Freedom + Own Safety	- Own Freedom + Family Safety	Global Human Rights	Respect Traditions	Less Globalization
Conflict	0.0198	0.0198	-0.00978	-0.0397	-0.0132	0.00599	0.0555	0.00724	0.0169
	(0.0397)	(0.0362)	(0.0432)	(0.0373)	(0.0337)	(0.0346)	(0.0343)	(0.0369)	(0.0410)
Observations	2,782	2,782	2,782	2,782	2,782	2,782	2,782	2,782	2,782
R-squared	0.027	0.032	0.036	0.018	0.025	0.038	0.037	0.059	0.062

The table presents estimates from OLS models. The outcome variables are stated in the first row. The sample compares the Conflict condition to the Health group and it includes only respondents in Germany, Italy and the Netherlands. Controls include gender, age groups, employment status, education, immigrant status, family status and number of family members, equivalised household income (coded into five quantiles), a dummy to define the position of the Macron Speech question (see Section 3.1 for more details) and country fixed effects. All controls are omitted to enhance readability. Robust standard errors clustered at the province level are in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table B49: Effects of the Conflict condition Spain - Trust

	Macron Speech	Trust Politicians	Social Trust	Trust Government	Trust Police	Trust Media	Trust Science	Trust EU
Conflict	-0.0339	0.139***	0.110	0.120**	0.0947**	0.122*	0.424***	0.137*
	(0.0488)	(0.0403)	(0.0780)	(0.0477)	(0.0388)	(0.0657)	(0.0785)	(0.0753)
Observations	881	881	881	881	881	881	881	881
R-squared	0.074	0.187	0.044	0.120	0.035	0.143	0.054	0.027

The table presents estimates from OLS models. The outcome variables are stated in the first row. The sample compares the Conflict condition to the Health group and it includes only respondents in Spain. Controls include gender, age groups, employment status, education, immigrant status, family status and number of family members, equivalised household income (coded into five quantiles), a dummy to define the position of the Macron Speech question (see Section 3.1 for more details) and country fixed effects. All controls are omitted to enhance readability. Robust standard errors clustered at the province level are in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table B50: Effects of the Conflict condition Spain - Taxation

	Regulate Markets	+Taxes -Poverty	+Taxes +Health Exp.	+Taxes +Unemp. Welf.	+Taxes +Pensions	Too Many Immigrants	Health Exp. to Natives	General Tax too High	Self Tax too High
Conflict	0.0127	0.0356	0.0530	0.0331	0.0355	-0.0398	0.00764	0.0689	0.0645
	(0.0364)	(0.0645)	(0.0591)	(0.0685)	(0.0504)	(0.0402)	(0.0542)	(0.0486)	(0.0565)
Observations	881	881	881	881	881	881	881	881	881
R-squared	0.072	0.015	0.067	0.066	0.053	0.044	0.028	0.137	0.131

The table presents estimates from OLS models. The outcome variables are stated in the first row. The sample compares the Conflict condition to the Health group and it includes only respondents in Spain. Controls include gender, age groups, employment status, education, immigrant status, family status and number of family members, equivalised household income (coded into five quantiles), a dummy to define the position of the Macron Speech question (see Section 3.1 for more details) and country fixed effects. All controls are omitted to enhance readability. Robust standard errors clustered at the province level are in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

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Table B51: Effects of the Conflict condition Spain - Voting

	Incumbent Voting	Populism Voting	Euroscept. Voting	Ideology Left/right	EU benefit	EU efficacy	Leave EU	Strong Leader	More Privacy	People Power	Free Media	Plutocra.
Conflict	-0.0477	-0.0518	-0.0460	-0.0513	-0.00304	0.102**	-0.103**	-0.00738	0.137***	-0.0214	0.0199	0.0340
	(0.0562)	(0.0561)	(0.0602)	(0.0702)	(0.0873)	(0.0491)	(0.0449)	(0.0547)	(0.0408)	(0.0814)	(0.0714)	(0.0743)
Observations	881	881	881	881	881	881	881	881	881	881	881	881
R-squared	0.014	0.084	0.069	0.070	0.084	0.083	0.060	0.046	0.031	0.033	0.080	0.052

The table presents estimates from OLS models. The outcome variables are stated in the first row. The sample compares the Conflict condition to the Health group and it includes only respondents in Spain. Controls include gender, age groups, employment status, education, immigrant status, family status and number of family members, equivalised household income (coded into five quantiles), a dummy to define the position of the Macron Speech question (see Section 3.1 for more details) and country fixed effects. All controls are omitted to enhance readability. Robust standard errors clustered at the province level are in parentheses.
* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table B52: Effects of the Conflict condition Spain - Identity

	Belong Town	Belong Nation	Belong EU	- Own Freedom + Public Safety	- Own Freedom + Own Safety	- Own Freedom + Family Safety	Global Human Rights	Respect Traditions	Less Globalization
Conflict	0.116	0.103*	0.0965	0.0772	0.0367	0.0429	-0.0804	0.157***	-0.0603
	(0.0727)	(0.0557)	(0.0607)	(0.0644)	(0.0629)	(0.0562)	(0.0552)	(0.0560)	(0.0558)
Observations	881	881	881	881	881	881	881	881	881
R-squared	0.043	0.027	0.039	0.020	0.029	0.035	0.040	0.067	0.050

The table presents estimates from OLS models. The outcome variables are stated in the first row. The sample compares the Conflict condition to the Health group and it includes only respondents in Spain. Controls include gender, age groups, employment status, education, immigrant status, family status and number of family members, equivalised household income (coded into five quantiles), a dummy to define the position of the Macron Speech question (see Section 3.1 for more details) and country fixed effects. All controls are omitted to enhance readability. Robust standard errors clustered at the province level are in parentheses.
* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

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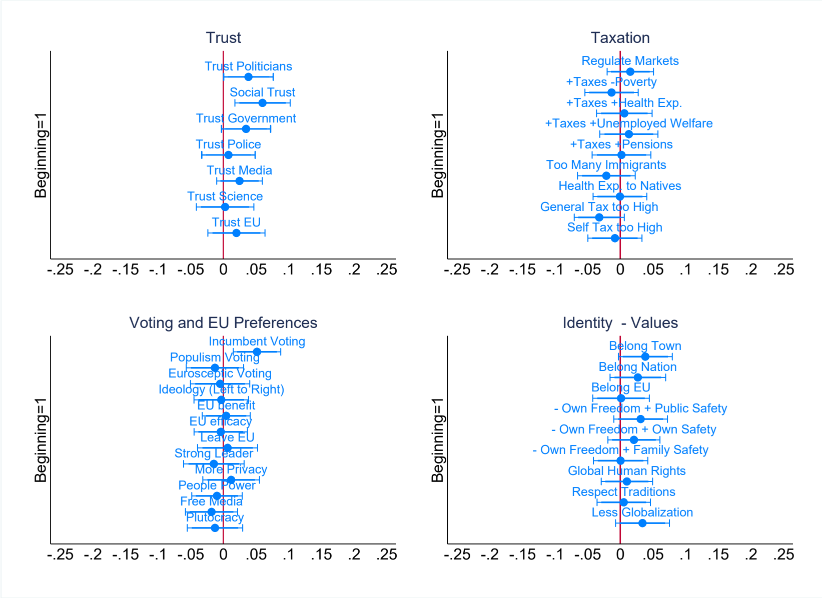
C Robustness analyses

C.1 Demand effects: the text agreement question

Figure C1 illustrates the coefficients associated to a dummy variable indicating whether the respondents were asked whether they wished to read the text about the European Union integration *before* or *after* they had answered our target outcome questions. The coefficients are statistically indistinguishable from zero in almost all cases, and they are small and unsystematic wherever they are significantly different at conventional levels. We interpret this finding as evidence that demand effects, intended as in respondents trying to provide answers in alignment with the perceived objectives of the experimenters, originating from the text agreement questions are small in our survey. As the question is explicitly asking the respondents to incur into effort and time costs to engage in an action that is explicitly pro-EU, we take the demand effects originating from this question as upper bounds to any demand effects potentially induced by the questionnaire itself.

Figure C1: Effect of the position of the text agreement question

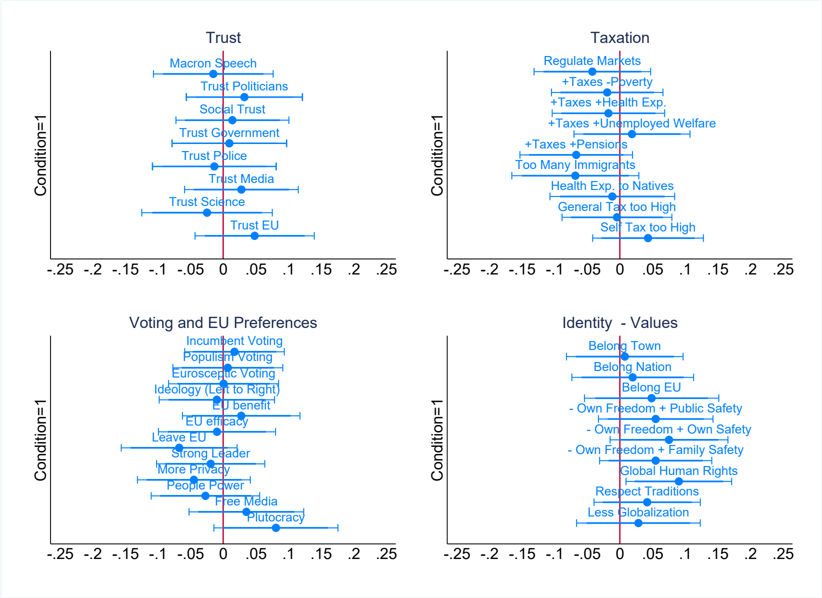


The figure displays the impact of the text agreement question being positioned at the very beginning of the socio-political attitudes block on the answers provided later in comparison to the answers provided in the socio-political attitudes block when the text agreement question is placed at the end of the block.

C.2 Placebo tests

Figures C2 and C3 present the impact on our target outcomes of participating in the Economic or Conflict conditions (see Section 3) rather than in the Health condition *after* having already answered the socio-political attitudes block of question. As participation occurs after the outcomes block, we expect no systematic impact of these conditions on our outcome variables. We observe that almost all of our effects are not significant at conventional levels, that they are small, and that they are not aligned with the impacts observed in our main analysis.

Figure C2: Placebo test of the Economic condition against the Health condition in the Baseline group



The figure displays the impact of participating in the Economic condition against participating in the Health condition in respondents who received the socio-political attitudes block of questions first and the COVID-19 block later. As the conditioning questions are asked later, they are expected not to impact the outcome responses.

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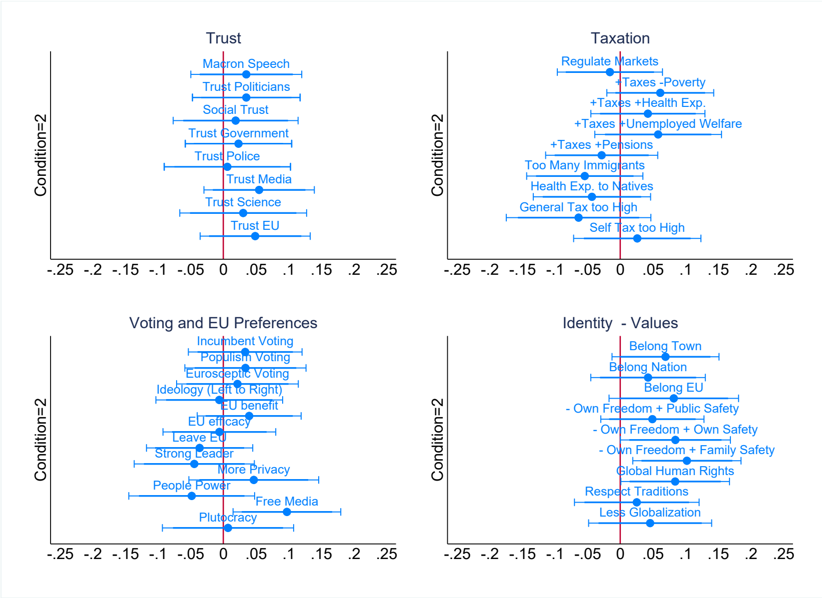
Figure C3: Placebo test of the Conflict condition against the Health condition in the Baseline group



The figure displays the impact of participating in the Conflict condition against participating in the Health condition in respondents who received the socio-political attitudes block of questions first and the COVID-19 block later. As the conditioning questions are asked later, they are expected not to impact the outcome responses.

D Factor analyses for the heterogeneity analysis

In Section 5.4 we study whether the effects of our conditions vary with individuals' experience with the COVID-19 epidemic. We specifically focus on the questions included in the health subcondition as these were asked to all respondents in the study.

We group these statements into three groups: i) having contracted the virus or having COVID-19 cases in one's close entourage: whether the respondents, someone in their family or acquaintances, has contracted the virus; ii) the degree to which the individual complies with the lock-down laws, including whether the respondent perceived social distancing rules as being too strict, kept social distancing and wore a mask; and iii) the degree to which the respondents are concerned with the epidemic, elicited as whether they tried to get or got tested for COVID-19 and as their self-reported level of concern about their health. We run a factor analysis on all questions in each group. In all three cases the factor analysis reveals the presence of a single factor upon which all elements load strongly (i.e. all factor loadings exceed 0.61).

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Group i) Included variables: Contracted the virus; COVID-19 cases in the family; COVID-19 cases among friends and acquaintances.

Factor	Eigenvalue	Explained variance	Rotated factor loadings		
			Contracted	Cases in family	Cases among friends
1 (retained)	1.43	0.48	0.67	0.76	0.63
2	0.87	0.29			
3	0.70	0.23			

Group ii) Included variables: social distancing rules are too rigid; respected social distancing rules; wore a face mask.

Factor	Eigenvalue	Explained variance	Rotated factor loadings		
			Rigidity	Respected distancing	Wore a mask
1 (retained)	1.42	0.47	-0.65	0.79	0.61
2	0.91	0.30			
3	0.67	0.23			

Group iii) Included variables: got tested for COVID-19; health related concern level.

Factor	Eigenvalue	Explained variance	Rotated factor loadings	
			Got tested	Concern
1 (retained)	1.14	0.57	0.75	0.75
2	0.86	0.43		

E The text agreement question: behavioural analyses

The analyses here presented follow the analytical framework outlined in Section 4.

Table E1 reports the summary statistics of the recorded time spent on the text screen by the respondents who chose to read the text. The Table disaggregates by Baseline and COVIDFIRST and by the subconditions of the latter. In order to obtain a more realistic picture, we trim the data by excluding from the analysis the upper tail of the distribution of time spent reading text: the top 1%. These are respondents who spent half an hour or more on the text screen.

Table E1: Summary statistcs of time in seconds spent by the respondents on the text screen

Condition	Mean	St. dev.
Baseline	204.56	248.75
COVIDFIRST	218.03	258.04
Health	217.57	264.42
Economic	213.72	242.40
Conflict	222.72	266.34

The respondents spent on average 213 seconds (slightly short of 4 minutes) on the text screen, with little variation across conditions.

Table E2 uses OLS analyses to look for differences in the amount of time spent reading the text across conditions. Differences in time spent on the text are mostly not significant at conventional levels, and where significant they are small in magnitude. The largest recorded difference is that observed between COVIDFIRST and the Baseline: Respondents in the former condition spent on average 13 seconds more on the text screen than respondents in the Baseline condition.

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Table E2: Effects of the treatment conditions on time spent reading the text

	(1)	(2)	(3)	(4)
Model	Time in seconds spent on the text screen			
(1): COVIDFIRST vs Baseline	13.03** (5.862)			
(2): Health vs Baseline		10.86 (8.155)		
(3): Economic vs Health			-3.010 (10.23)	
(4): Conflict vs Health				7.160 (10.74)
Observations	5,799	3,313	2,513	2,535
R-squared	0.024	0.025	0.022	0.031

The table presents estimates from OLS models. The outcome variable is the time in seconds spent reading the text about European integration. The regressions compare time spent on the text between COVIDFIRST and Baseline, between Health and Baseline, between Economic and Health and between Conflict and Health. We exclude respondents who are recorded to spend more than 1849 seconds (30.8 minutes) on the text screen. Controls include gender, age groups, employment status, education, immigrant status, family status and number of family members, equivalised household income (coded into five quantiles), a dummy to define the position of the Macron Speech question (see Section 3.1 for more details) and country fixed effects. All controls are omitted to enhance readability. Robust standard errors clustered at the province level are in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

In Figure E1 we compare the distributions of the text ratings in, respectively, the COVIDFIRST and Baseline, the Health and Baseline, the Economic and Health and in the Conflict and Health conditions.

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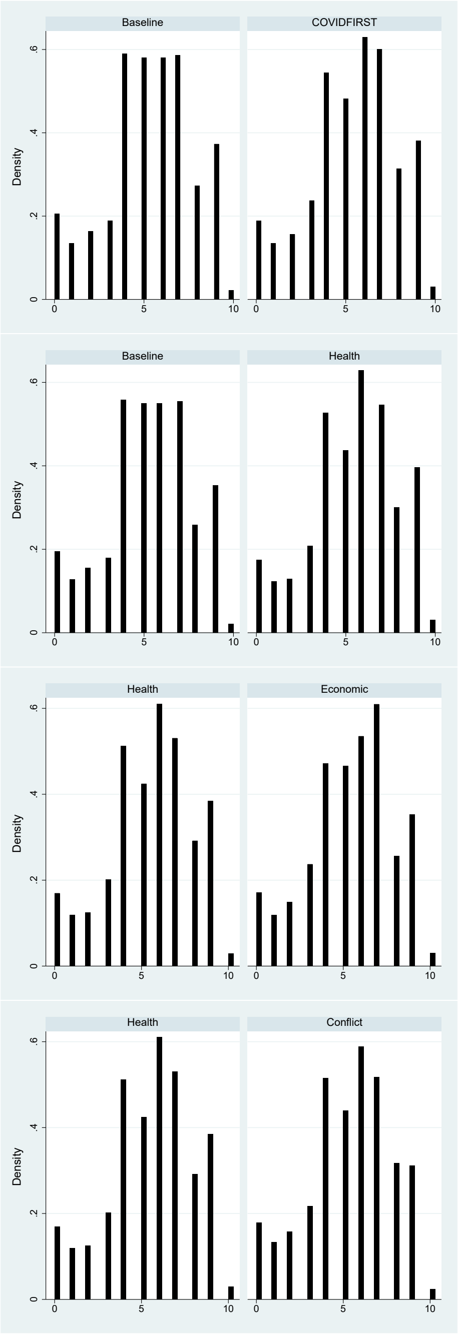
Figure E1: Distribution of text ratings in the COVIDFIRST and Baseline conditions



The figure shows the distribution of the ratings assigned to the text about European integration assigned by the respondents who agreed to read the text across the four study conditions: i) Covidfirst Vs baseline; ii) Health Vs baseline; Economic Vs Health; Conflict Vs Health. We exclude respondents who are recorded to spend more than 1849 seconds (30.8 minutes) on the text screen.

As evident from the Figures, the distributions are extremely similar in all cases. Two-sided Kolmogorov-Smirnov tests cannot reject the null hypothesis of equality of the populations in three out of four cases. P-values are reported in Table E3.

Table E3: Kolmogorov-Smirnov tests: equality of the distribution of text ratings

	COVIDFIRST vs Baseline	Health vs Baseline	Economic vs Health	Conflict vs Health
Two-sided p-values	0.118	0.060	0.973	0.794

The table reports the two-sided Kolmogorov-Smirnov tests of distribution equality of the ratings assigned to the Euroepean integration text by the respondents who chose to read it. We exclude respondents who are recorded to spend more than 1849 seconds (30.8 minutes) on the text screen.

Finally, we investigate whether a relationship exists between the rating assigned to the text and the time spent reading it among those who chose to do so. Table E4 reports the results of an OLS regression. Not surprisingly those who assigned a greater rating also spent a significantly larger amount of time reading the text. Notice however that though precisely estimated, the coefficient is small: an additional 30 seconds increases the score by 0.02 points.

Table E4: OLS regression of the rating assigned to the text on the time spent on the text screen

	(1) Rating assigned
Time in seconds spent on the text screen	0.000871*** (0.000151)
Observations	5,799
R-squared	0.025

The table presents estimates from OLS models. The outcome variable is the rating assigned to the text about European integration. We exclude respondents who are recorded to spend more than 1849 seconds (30.8 minutes) on the text screen. Controls include gender, age groups, employment status, education, immigrant status, family status and number of family members, equivalised household income (coded into five quantiles), a dummy to define the position of the Macron Speech question (see Section 3.1 for more details) and country fixed effects. All controls are omitted to enhance readability. Robust standard errors clustered at the province level are in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

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F Questionnaire

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Covid-19 and Europeans' Attitudes towards EU intervention

Investigators:
- Gianmarco Daniele, Università Bocconi, Università di Milano;
- Andrea Martinangeli, Max Planck Institute for Tax Law and Public Finance;
- Francesco Passarelli, Università Bocconi, Università di Torino;
- Willem Sas, University of Stirling, KU Leuven;
- Lisa Windsteiger, Max Planck Institute for Tax Law and Public Finance;

Survey location: Italy, Spain, Germany, Netherlands

Target sample: random sample of the adult population representative over age, gender and income (2000 respondents per country)

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Survey questionnaire draft

We are non-partisan researchers from an independent research institute.
We would like to know your **personal views** on matters of public interest.
It is very important that you provide your **true opinion**, and that you **read all the questions very carefully before answering**. If you do not know the answer to some question, please provide us with a careful guess. However, please be sure to spend enough time reading and understanding the question. Responding without adequate effort or skipping many questions may result in your responses being flagged for low quality and you may not receive your payment.
It is very important that you **complete the entire survey,** once you've started. It should take approximately 20 minutes to complete.

Note: Your participation in this study is purely voluntary. No identifying information will be recorded by the researchers. Results may include summary data, but you will never be identified. The data will be stored on our servers and will be kept confidential. The anonymous data collected may be made available to other researchers for replication purposes.

1. Yes, I would like to participate in this survey. / No, I would not like to participate in this survey.
2. What is your gender? (M/F)
3. Please indicate your age:
4. What is your area of residence? [Country dependent]
North, NorthE, NorthW, Centre, South, Islands
5. What is your marital status?
   a. Single (Never Married/Widowed/Separated/Divorced)
   b. Married /Civil partnership/Cohabiting
6. Please indicate how many people live in your household (including yourself): Adults… Children…
7. What is the combined **monthly** income of your **household, after taxes**?
[Please include all your household income sources: salaries, scholarships, pension and Social Security benefits, dividends from shares, income from rental properties, child support and alimony etc. We are not interested in the type of income source, only in the total monthly income earned by all the members of your household together.]
   1. <2000
   2. 2000-4000
   3. 4000-6000
   4. 6000-8000
   5. 8000-10000
   6. >10000

8. [Country] is divided into regions [Italy]/provinces [Netherlands]/länder [Germany]/regions [Spain]. How many regions have you visited at least once in the past 12 months besides your own? This question's only purpose is that of allowing us to check the quality of the answers we received so far. To continue with the questionnaire, please enter 30 to proceed with the questionnaire.

/----------------- THE ORDER OF BLOCK 1 AND BLOCK 2 IS RANDOMISED----------------------------/

++++BLOCK 1: TREATMENT QUESTIONS

QUESTIONS TREATMENT GROUP T1: Health/Crisis experience

10. On a scale from 1 to 10, to what extent do the following statements describe your behavior during the COVID-19 confinement period? (1= not at all; 10= a lot)
    a. I worked from home
    b. I kept more distance with people than usual
    c. I stocked up on food
    d. I bought face masks
    e. I cleaned my house/apartment with disinfectant products
    f. I tried to get or got tested for COVID-19
    g. I have donated or volunteered to help combat COVID-19

11. Do you have relatives who are risk patients of COVID-19?
    a. Yes
    b. No
    c. Don't know

12. Please indicate whether the following applies to you:
    a. I contracted the virus (YES/NO/DON'T KNOW)
    b. Someone in my family or close to me has contracted the virus (YES/NO/DON'T KNOW)
    c. At least one of my friends/acquaintances has contracted the virus (YES/NO/DON'T KNOW)

13. On a scale from 1 to 10, do the following statements about the COVID-19 confinement apply to you personally? (1= not at all; 10= a lot)
    a. Living together with my family/household was difficult
    b. I was concerned about my health
    c. Not seeing my friends or family was difficult
    d. I thought the social isolation rules were too strict

14. On a scale from 1 to 10, and when you think about the COVID-19 crisis, how much of your time did you feel:
    a. Relaxed (1= never, 10= always)
    b. Angry (1= never, 10= always)
    c. Nervous (1= never, 10= always)
    d. Active (1= never, 10= always)
    e. Anxious (1= never, 10= always)

QUESTION ONLY FOR T1

15. Which of the following appliances do you have in your house/flat?
    a. PC/laptop (Yes/No)
    b. TV (Yes/No)
    c. Microwave (Yes/No)
    d. Internet (Yes/No)
    e. Airconditioning (Yes/No)
    f. Refrigerator (Yes/No)

QUESTIONS TREATMENT GROUP T2: T1 + Economic distress

16. On a scale from 1 to 10, and when you think about COVID-19 crisis, do you think that
    a. there were problems with food supplies in [Country] (1= not at all; 10= a lot)

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b. There will be negative financial consequences for yourself and your family in the future (1= not at all; 10= a lot)
c. There will be negative financial consequences for the town in which you live in the future (1= not at all; 10= a lot)

17. Is the COVID-19 crisis affecting your job?
    a. Yes, mostly positively
    b. Yes, mostly negatively
    c. Not significantly
    d. I don't have a job

18. Is the COVID-19 crisis affecting the job of people close to you?
    a. Yes, mostly positively
    b. Yes, mostly negatively
    c. Not significantly

19. If you would lose your job because of the crisis, how quickly do you think you would find a new job once the economy picks up?
    a. In a few weeks
    b. In a few months
    c. After a year

QUESTIONS TREATMENT GROUP T3: T1 + National Unity/Warspeak

20. On a scale from 1 to 10, do you agree with the following statements? (1= not at all; 10= a lot)
    a. The COVID-19 epidemic can be considered a war in which the enemy is COVID-19
    b. We can defeat COVID-19 only if everyone self-sacrifices, e.g. by strictly respecting self-isolation at home
    c. Healthcare personnel are the frontline soldiers, and each of us is fighting at the home-front by self-isolating and respecting the rules
    d. People breaking the rules can be considered traitors and should be punished
    e. Unity is the main strategy to defeat the COVID-19 crisis
    f. Vaccine research is the best weapon we have, to defend us against the virus

++++BLOCK 2: OUTCOME VARIABLE QUESTIONS

VOTING

21. Imagine the national elections were coming up next [Sunday]. Which party would you vote for? [insert parties per country – this version: Italy]
    a. Lega
    b. Partito democratico
    c. M5S
    d. Forza Italia
    e. Fratelli d'italia
    f. Italia viva
    g. Altro. Specificare:_____
    h. Non voterei

TRUST

22. On a scale from 1 to 10, do you think one can never be careful enough in dealing with people (1), or would you say that most people can be trusted (10)?

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NATIONAL SUPPORT

23. On a scale from 0 to 10, how much do you trust each of the following: (1= not at all; 10= complete trust)
    a. Your national politicians
    b. Your national government
    c. The police
    d. Your public broadcaster
    e. Your national scientists/experts

ATTACHMENT

24. People may feel different degrees of attachment to their town or village, to their country or to Europe. On a scale from 1 to 10, how attached do you feel to
    a. [Country] (1= not at all, 10= a lot)
    b. Your town/village (1= not at all, 10= a lot)
    c. Europe (1= not at all, 10= a lot)

EU SUPPORT

25. On a scale from 1 to 10, how much do you trust the European Union (1= not at all, 10= a lot).

26. On a scale from 1 to 10, would you say that [Country] has benefited from being a member of the European Union? (1= not at all, 10= a lot)

27. If there was a referendum next Sunday with the following question: "Should [Country] remain a member of the European Union or leave the European Union", how would you vote?
    a. Remain in the European Union
    b. Leave the European Union
    c. I don't know

28. On a scale from 1 to 10, do you think the EU is better placed to solve problems than national or regional governments are? (1= not at all; 10= best placed)

IMMIGRATION

29. On a scale from 1 to 10, do you think current immigration in your country is too low (1) or too high (10)?

30. On a scale from 1 to 10, how much do you think the public healthcare system in your country should prioritise [nationality] over immigrants (1= not at all, 10= a lot)

GOVERNMENT

31. People have different views on what the responsibilities of the government should or should not be. On a scale from 1 to 10, do you think the government should
    a. raise taxes to subsidise the poor (1= not at all; 10= a lot)
    b. regulate markets (1= not at all; 10= a lot)
    c. raise taxes to ensure adequate unemployment insurance (1= not at all; 10= a lot)
    d. raise taxes to ensure adequate health care (1= not at all; 10= a lot)
    e. raise taxes to ensure a reasonable standard of living for the old (1= not at all; 10= a lot)

32. On a scale from 1 to 10, would you say that
    a. the *overall* fiscal burden in your country is too low (1) or too high (10)?
    b. *your* fiscal burden is too low (1) or too high (10)

LIBERALISM vs POPULISM

33. On a scale from 1 to 10, do you agree with the following statements? (1= fully disagree; 10= fully agree)
    a. Privacy rights should always be upheld/protected, even if they hinder efforts to combat crime.
    b. The people, and not politicians, should make our most important policy decisions.
    c. Politicians should have no influence over the content of public broadcasters.
    d. Having a strong leader is good for [Country] even if this leader breaks the rules to obtain results.
    e. A handful of powerful individuals influences political decisions even in democracies.

34. How much of your personal freedom would you be willing to give up to
    a. protect your own safety? (1= none; 10= a lot)
    b. protect the safety of your family? (1= none; 10= a lot)
    c. protect public safety? (1= none; 10= a lot)

UNIVERSAL vs COMMUNAL

35. On a scale from 1 to 10, do you agree that
    a. everyone should be treated equally as global citizens, with fundamental rights (1= not at all; 10= fully agree)
    b. everyone should be loyal to the community they are part of, and respect its traditions (1= not at all; 10= fully agree)

GLOBALISATION

36. People have different views about market globalization. On a scale from 1 to 10, do you favour completely globalised markets (1), complete national self-sufficiency (10).

TEXT QUESTION HERE (see end of document for details; randomly placed here or at the beginning of block 2)

EU SUPPORT: COVID

37. On a scale from 1 to 10, do you think the European Union is managing the COVID-19 epidemic well? (1= not at all, 10= absolutely)

38. On a scale from 1 to 10, do you think your national government is managing the COVID-19 epidemic well? (1= not at all, 10= absolutely)

39. Which of the following should mostly fund the economic consequences of the COVID-19 crisis?
    a. Your national government
    b. The European Union
    c. Your regional government

40. On a scale from 1 to 10, do you think there should be solidarity between EU member states to fund the COVID-19 costs? (1= there should not be; 10= there should be)

/------------------------------- END OF TREATMENT BLOCKS ---/

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OTHER

41. Which media do you most frequently get information on world happenings from?
(If you don't find your preferred outlet, please indicate the one that most closely represents it)
    a. TV News
    b. Social media (social networks, blogs)
    c. Radio/podcasts
    d. Online newspaper/newspaper app
    e. Print newspaper
    f. I don't follow the news

42. What is the highest level of education you have completed?
    a. Primary school
    b. Junior high school (middle school)
    c. Professional education
    d. Higher education (science/humanities)
    e. University degree
    f. Doctoral degree

43. What is your current employment status?
    a. Employed full-time
    b. Employed part-time
    c. Self-employed/small business owner
    d. Unemployed and looking for a job
    e. Not working and not looking for a job/Long-term sick or disabled
    f. Full-time parent, homemaker
    g. Retired
    h. Student/Pupil

44. Were you born in [Country]?

45. Were both of your parents born in [Country]??

46. What is your province of residence?

47. Where do you see yourself on the political spectrum, where 1 represents the left and 10 represents the right?

48. Did you vote in the last election?

TEXT QUESTION:

For educational purposes, we are considering to inform students about the importance of the European Union using real texts.
We selected a speech given in front of the European Parliament, which promotes European integration.
It would help us if you could take 5 minutes of your time to read this speech and give us your opinion. Please notice that whether you agree to read the text or not will not affect your payment.

Yes, I want to read the text.
No, I don't want to read the text.

Next page: Thank you very much for your help, you will get to read the speech and give your opinion at the end of this survey.

At the end of the survey (if they clicked yes):

Thank you for agreeing to review the speech on EU integration which we plan to use for educational purposes. You can find the speech below. You will be able to provide us with your opinion on the next page.

Speech is displayed.

Question after speech:
On a scale from 1 to 10, do you think this text, a speech held by Emmanuel Macron in 2018, can be used to inform students of the advantages and importance of the European Union? (1= No, 10=Yes)

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CEPR PRESS

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Did the COVID-19 Pandemic trigger nostalgia? Evidence of Music Consumption on Spotify

Timothy Yu-Cheong Yeung[1]

Date submitted: 21 August 2020; Date accepted: 22 August 2020

By scraping data of almost 17 trillion plays of songs on Spotify in six European countries, this work provides evidence that the lockdown imposed in the midst of the COVID-19 pandemic significantly changed the music consumption in terms of nostalgia. This work constructs a binary measure of nostalgia consumption of music and employs country-specific logistic regressions in which lockdown is taken as a treatment that interacts with a quadratic trend. The lockdown altered the trend of nostalgia consumption upward, which peaked roughly 60 days after the lockdown. A placebo test shows that the upward turn of slope is not an annual pattern. On the other hand, COVID incidence rate does not provide significant additional explanatory power to the model. This work shows that Spotify's users react to the lockdown even when COVID incidence rate is low and the impact stays high even the incidence rate has peaked, suggesting that demand for nostalgia tends to respond to the drastic and lasting change caused by the lockdown rather than to the fluctuations in the viral infection.

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1 Postdoctoral Research Fellow, Faculty of Law, KU Leuven, Leuven, Belgium

1 Introduction

A comment on Radiohead's 1995 classic *Fake Plastic Trees* YouTube video by an user Luiza Martins:

> "Who is listening to this song in quarantine against covid-19? :D"

attracted more than 2600 likes in four months time since April 2020. Many other examples could be found in other music videos.

Did the COVID-19 pandemic trigger widespread nostalgia? Nostalgia was considered as a form of melancholia or depression (McCann, 1941; Rosen, 1975). Gradually researchers move on to recognize the causes and the positive aspects of nostalgia. Researchers found that negative moods trigger nostalgia and nostalgia induces positive affects (Wildschut et al., 2006), while sadness predicts nostalgia (Barrett et al., 2010). Given its scale and the adverse socio-economic impact caused (Martin et al., 2020), it is natural to hypothesize that the COVID-19 pandemic induced a widespread nostalgic feeling.

A crisis, either personal, national or global, certainly changes human behaviors and in particular consumption pattern. Women tend to consume more on beauty products during recessions, known as lipstick effect in consumer psychology that could be explained by mating and professional motives (Hill et al., 2012; Netchaeva and Rees, 2016). Unemployment is found to correlate with heavier alcohol and drug consumption (Layne and Whitehead, 1985; Janlert and Hammarström, 1992; Power and Estaugh, 1990; Henkel, 2011), though Catalano et al. (2011) challenged and claimed that the answer remains mixed. Although music is often discussed and consumed alongside alcohol, the academic literature is silent on the change in music consumption during a time of difficulty. If alcohol consumption is considered as a remedy, music could also take this role. Drinking is arguably an effective way to forget the present difficulties, to avoid dealing with current problems and to keep one's world isolated from others. Music could also achieve partially these goals. Music of the past can in addition bring in nostalgia or reminiscence that contributes to certain healing effects (Barrett et al., 2010; Lazar et al., 2014). Music therapy aiming at evoking nostalgia has been shown effective towards patients of dementia (Glynn, 1992; Mills and Coleman, 1994; Beard, 2012).

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Nostalgia has long been a research topic in consumer psychology (Holbrook, 1993; Holbrook and Schindler, 2003; Sierra and McQuitty, 2007; Holak et al., 2007) and marketing strategies based on nostalgic feelings have been widely adopted (Unger et al., 1991; Russell, 2008; Cui et al., 2015). Hirsch (1992) suggested that by defining nostalgia as a yearning for an idealized past, nostalgia marketing induces displacement of idealized past emotions onto objects. Difficult times are thus the successful times for nostalgia marketing that alludes to a better past (Spaid, 2013).

The COVID-19 pandemic has undoubtedly altered consumers' consumption patterns (Hall et al., 2020; Baker et al., 2020) and affected heavily the consumption on cultural goods. Sim et al. (2020) studied the music consumption on Spotify of 60 countries and found that music consumption online had declined during the COVID-19 pandemic. Weed (2020) discussed the cancellation of sport events had led TV channels to replay matches in the past and discussed the potential restorative nature of such a form of lockdown nostalgia in supporting well-being during the lockdown. Gammon and Ramshaw (2020) discussed the role of nostalgia consumption during the COVID-19 pandemic. The current work is, to the best of the author's research, the first quantitative study of nostalgia consumption of music during the COVID-19 pandemic.

The pandemic manifests itself in many dimensions of our daily life. The viral infection is only the surface layer and in fact does not impact directly most of the population. Instead, the threat of the virus and the resulting distress has substantially changed the costs and benefits of our behaviors. Since some people were reluctant or not willing to comply to orders or to keep social distance, governments took actions to impose exceptional measures and even "locked down" a whole nation. Under a lockdown or a quarantine, people's freedom is heavily limited and physical interactions among people outside their close families are almost non-existent. For example, under the Belgian national lockdown order, citizens were required to stay at home and to go out of doors only for reasons deemed "essential".[1] Outdoor exercise was still allowed, provided that social distancing guidelines were upheld. Temporary police check points were set up to ensure that citizens complied with the rules. The measures adopted by Belgian authorities were, in several respects, less restraining than those enacted by neighboring countries. In France, citizens were required to sign a document attesting the reason for going out of doors

[1]Details of the measures can be found at https://www.belgium.be/en/news/2020/coronavirus_reinforced_measures.

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and were only permitted to roam within one kilometer of their home for an hour each day. Children in Spain were barred from leaving home for nearly two months. The scale of the lockdown is unprecedented. The lockdown and the viral infection should not be considered equivalent in determining human behaviors and estimations of their respective effects are the focus of the current work.

To quantify nostalgia seems to be a prohibitive challenge. This work measures nostalgia by an individual's music consumption on a popular music streaming platform *Spotify*. Spotify publishes daily charts of top 200 songs of different countries and, through its API, users can scrap the information of the tracks. Each song is associated with its release information on which this work arbitrarily classifies a song as a nostalgia consumption if the number of days since release is more than 1095 days (3 years).[2] Using COVID incidence rate and taking lockdown as a treatment that interacts with a quadratic trend, a logistic regression weighted by number of plays is employed to explain nostalgia consumption of music based on the information of the daily top 200 tracks over a period of seven months.

The current work finds that nostalgia consumption took a sharp upward change in the beginning of the lockdown and fell when time went on and COVID incidence rate does not significantly improve the model's explanatory power. This work aims to discover individuals' consumption preference on cultural goods, music in this particular case, and to provide evidence of nostalgic consumption during a time of widespread difficulty. Last but not least, this work points to a possible and relatively low-cost remedy in the time of the pandemic.

2 Data

Spotify is a Swedish music streaming platform, publicly traded in the NYSE through the holding company *Spotify Technology S.A.* Since 2008, Spotify has provided access to over 60 million songs on which users enjoy free service with advertisements. Paying subscribers, like Netflix users, pay a fixed monthly subscription fee and thus enjoy offline and advertisement-free listening. The company announced in July 2020 that active users reached 299 million whereas 138

[2] Results based on different definitions of nostalgia consumption, e.g. five years instead of three years, multiple levels of nostalgia, etc., are similar.

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million users are paying subscribers.[3][4] Number of plays is massive. Top 200 songs in the UK in total were played 20 million times on an average day in 2020.[5] Along with its rise in popularity, Spotify has increasingly drawn attention from the academia (Vonderau, 2019; Mähler and Vonderau, 2017; Meier and Manzerolle, 2019), thanks to its easy-to-use API data query system.

This work fixes the sample period between 1 January and 31 July 2020. The COVID-19 pandemic hit hard most of the European countries in March 2020 and in succession they went into certain forms of lockdown (or a less dramatic term: confinement). The peak of the first wave passed roughly in May and the situation improved significantly towards July. By the end of July, there were signs of a second wave.[6] The sample period is arguably sufficiently long to capture the initial shock and the subsequent adjustment back to the norm. This research relies on data of six European countries, namely, Belgium, France, Italy, Spain, Sweden and United Kingdom, involving almost 17 trillion of plays. These countries, except Sweden, had been under some forms of national lockdown from March to May. Some brief information on the lockdown is provided in Table 1. Although scraping data of some more countries is not a difficult or time-consuming task, this work limits itself to these six countries for two reasons. First, as readers will see in later sections, countries experienced very different music consumption patterns, not only in quantity but also in quality in terms of nostalgia level. Pooling countries into one single sample may not be an appropriate approach, though gathering more information and working with a panel of countries are possible. Second, big nations, for examples, the US, Canada and Australia, had experienced multiple outbreaks of COVID infection at different points of time within the nation and thus lockdown measures were not uniform across the nation. Spotify, on the other hand, does not provide regional consumption information. The misalignment of data aggregation level casts doubt on the validity of such an analysis. The six countries chosen include two heavily affected countries that went into lockdown relatively earlier, Italy and Spain, two less severely affected countries but also went into tight lockdown, France and Belgium, the UK, who reacted relatively later than others, and Sweden, who had not been into restrictive lockdown. Sweden is chosen in the hope that it could serve as a control country.

[3] https://newsroom.spotify.com/2020-02-05/spotify-reports-fourth-quarter-and-full-year-2019-earnings/
[4] https://www.bbc.com/news/technology-52478708
[5] Author's own computation
[6] https://www.bbc.com/news/av/uk-53568967/coronavirus-johnson-says-signs-of-a-second-wave-showing-in-europe

Spotify publishes daily the top 200 mostly played songs of different countries along with their numbers of plays. Through its API, information on songs' release date is available. A song is defined as a nostalgia consumption if the number of days since release is larger than 1,095 (three years). Figure 1 illustrates the average nostalgia level of the daily top 200 songs of the six countries from 1 August 2018 to 31 July 2020, along with a red vertical line corresponding to the first lockdown day.[7] The average nostalgia level surges in Christmas time and rises gradually after the lockdown. Sweden sees another annual spike in nostalgia consumption of music on the Midsummer Day. To check if the rise during the lockdown is not a annual pattern, Figure 2 matches the average nostalgia level of 2020 and 2019 to the January-July period and shows that, while the case in Sweden is unclear, other countries recorded a higher average nostalgia level in the same period of 2020.

A very first challenge to any correlation between the pandemic and nostalgia consumption is that music companies may publish fewer songs during the pandemic because advertising may heavily be affected. If no hit new songs are supplied to the market, users may revisit older songs to satisfy their demand for music. Figure 3 illustrates the numbers of new tracks among the top 200, defined as released within 30 days before the day of observation, from January 2020 to July 2020, overlaid with the 7-day moving-average of daily new COVID-19 cases per million of population (incidence rate). Counts of daily new COVID-19 cases are collected from EU Open Data Portal.[8] Any fall in the number of new tracks among the top 200 does not perfectly reflect fewer releases of new songs as the chart is certainly endogenously determined. However, the three-year threshold that defines nostalgia consumption is sufficiently far from the day of the observation, any correlation between the pandemic and nostalgia consumption is thus not directly driven by number of new releases. Imagine a hypothetical day having no additional new release. Users' preference may remain unchanged and listen to the same songs so that the overall nostalgia level is the same. Only when people switch to older songs (more than 1,095 days) the overall average nostalgia level would go up. Still, fewer new releases may induce an indirect effect on nostalgia consumption because new songs occupy users' time that would have been consumed on nostalgic songs. Although number of new releases arguably fell together with a rise in COVID infection, whether it is causal is far from clear. Number of new releases seems to be low in the beginning of the year and gradually increases over the

[7] The red line of Sweden corresponds to the date of travel advice within the nation on 24 March.

[8] https://data.europa.eu/euodp/en/data/dataset/covid-19-coronavirus-data

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first quarter. A subsequent adjustment possibly follows in the second quarter, coinciding with the rise in COVID infection. In the following regression analysis, the number of new tracks among the top 200 released within the past 30 days will always be included as a control variable.

Table 1: Lockdown Information

Country	Implementation Date	First Relaxation Date	Measures
Belgium	18 March	11 May	Restrictive Quarantine
France	17 March	11 May	Restrictive Quarantine
Italy	10 March	4 May	Restrictive Quarantine
Spain	14 March	11 May	Restrictive Quarantine
Sweden*	18 March	NA	Mild and Voluntary
United Kingdom	24 March	10 May	Restrictive Quarantine

*Sweden had no tight lockdown measures but social distancing and travel advices.

Another concern is about the compositions of users pre-lockdown and in-lockdown are different. Lockdown may draw new users to the platform, perhaps due to having more abundant free time, who tend to listen to older songs. While it is impossible to identify users, data, as shown in Figure 4, suggest that the pandemic caused music consumption to fall, consistent with the finding by Sim et al. (2020). While Belgium saw the number being stable, France, Italy and Spain recorded a dip in the beginning of the lockdown. In the meantime, Sweden and the UK followed their pre-lockdown downward trend. Spikes of plays during the Christmas time in Belgium, Sweden and the UK coincide with spikes in nostalgia consumption. Holiday effects seem to be present, which may then affect the average nostalgia consumption.

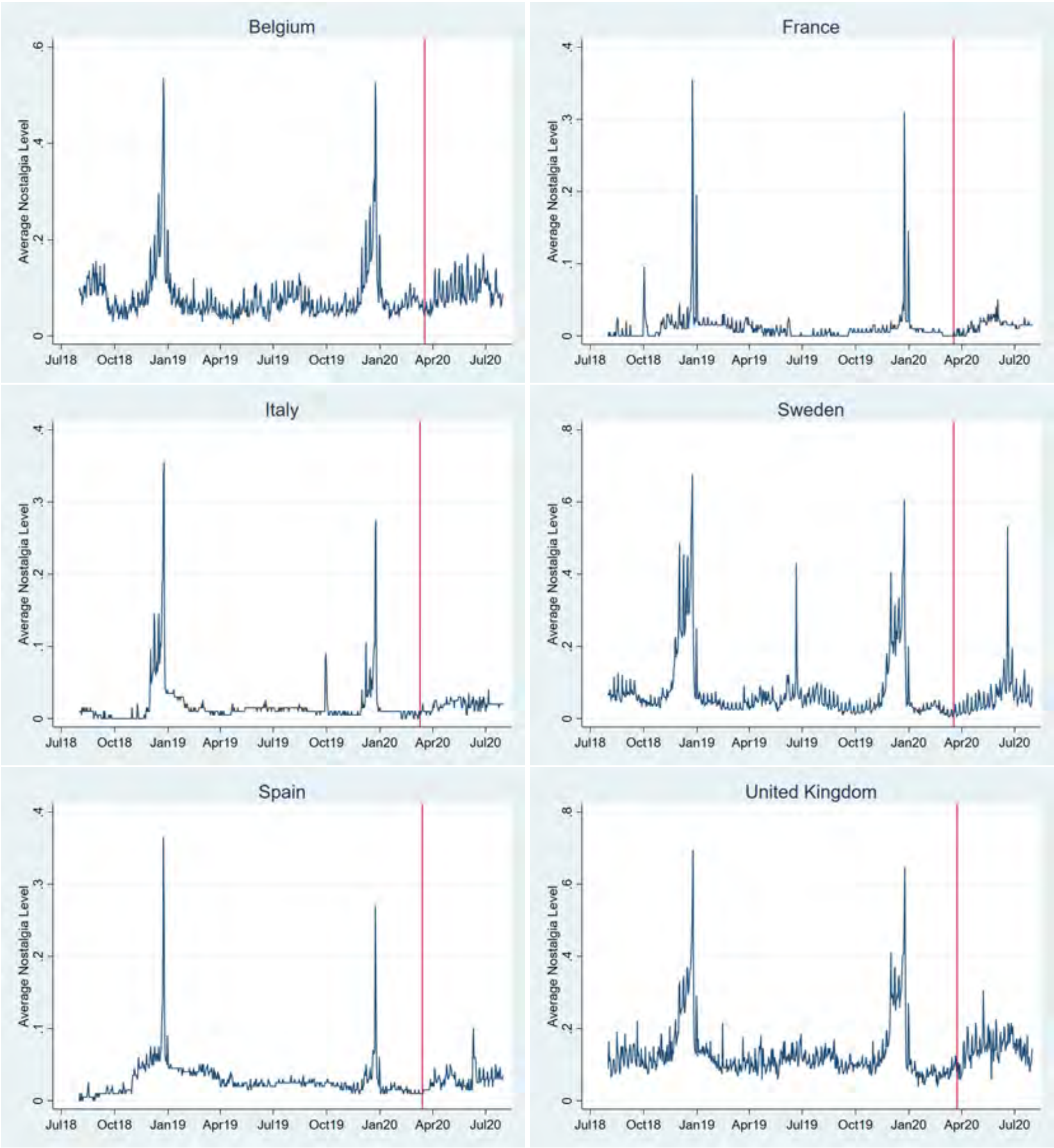
Based on the discussion above, any valid regression analysis should take into account seasonal patterns, issues of new tracks and total number of plays. Moreover, any effects of lockdown may not show up right at the beginning of the lockdown period, but gradually reflected by an upward trend.

3 Empirical Analysis

3.1 Empirical Strategy

The empirical analysis will rely on country-specific logistic regressions. Each play is a choice between a set of nostalgic songs (released more than 1,095 days before the day of observation,

Figure 1: Nostalgia Level August 2018 - July 2020



t) and a set of new songs (released within 1,095 days before day t). The actual implementation is a logistic regression in which the dependent variable (nostalgia consumption = 1) weighted by number of plays. The main explanatory variable is the lockdown indicator (equals 1 if the lockdown implementation day $t^L \leq t$, and 0 otherwise). Note that the no ending date of the lockdown has been coded. The very first reason is that lockdown was gradually relaxed and

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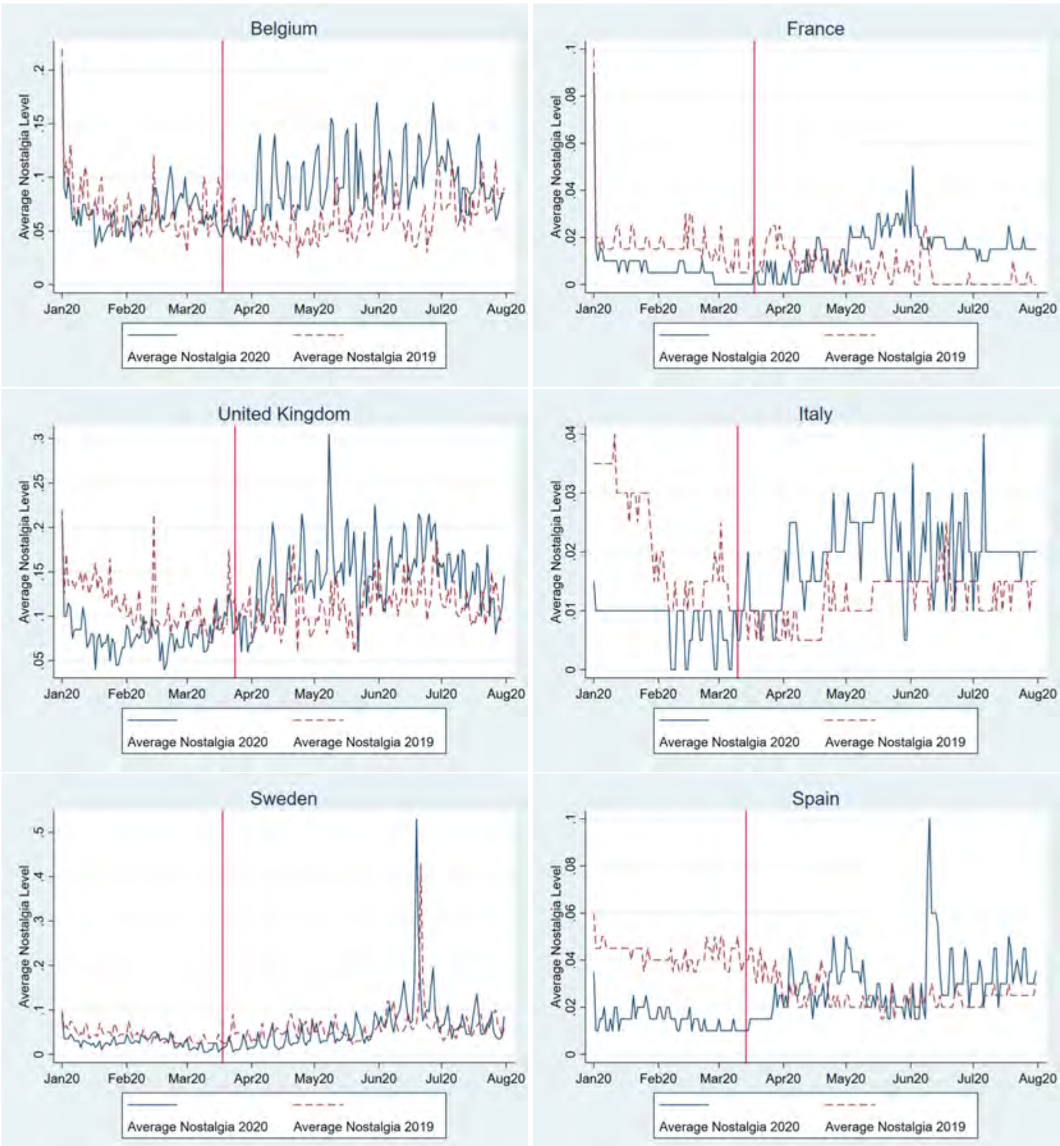
Figure 2: Nostalgia Level January 2020 - July 2020 compared to the same period of 2019



the degress of relaxation varies across countries. Secondly, lockdown was announced only a day before the actual implementation because the governments wanted to minimize choatic traffic as much as possible, but the relaxation in phases was announced a week or some weeks before the implementation. One would expect the lockdown induced a shock but the relaxation would only lead to gradual adjustment. As our model allows a quadratic trend during the in-lockdown

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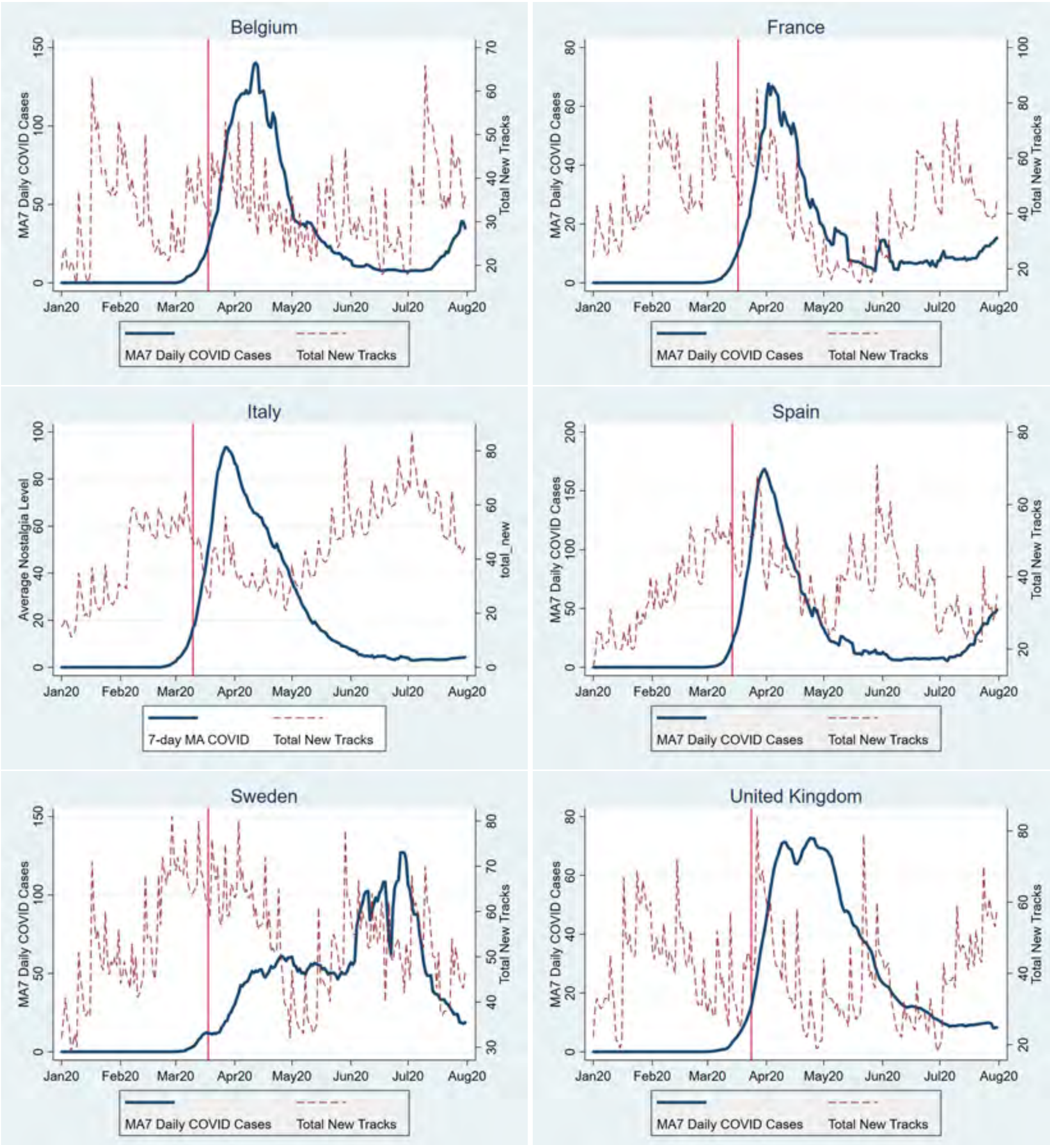
Figure 3: Numbers of New Tracks and COVID Infection, January 2020 - July 2020



period, it should be able to capture the non-linear variation from the beginning of the lockdown to the gradual relaxation towards June and July. Another explanatory variable of interest is the COVID incidence rate, which is precisely the natural logarithmic transformation of the 7-day moving-average of the number of daily new COVID cases per million of population.[9] This work

[9]The 7-day MA is computed by averaging the numbers of new COVID cases per million of the past six days and that of day t.

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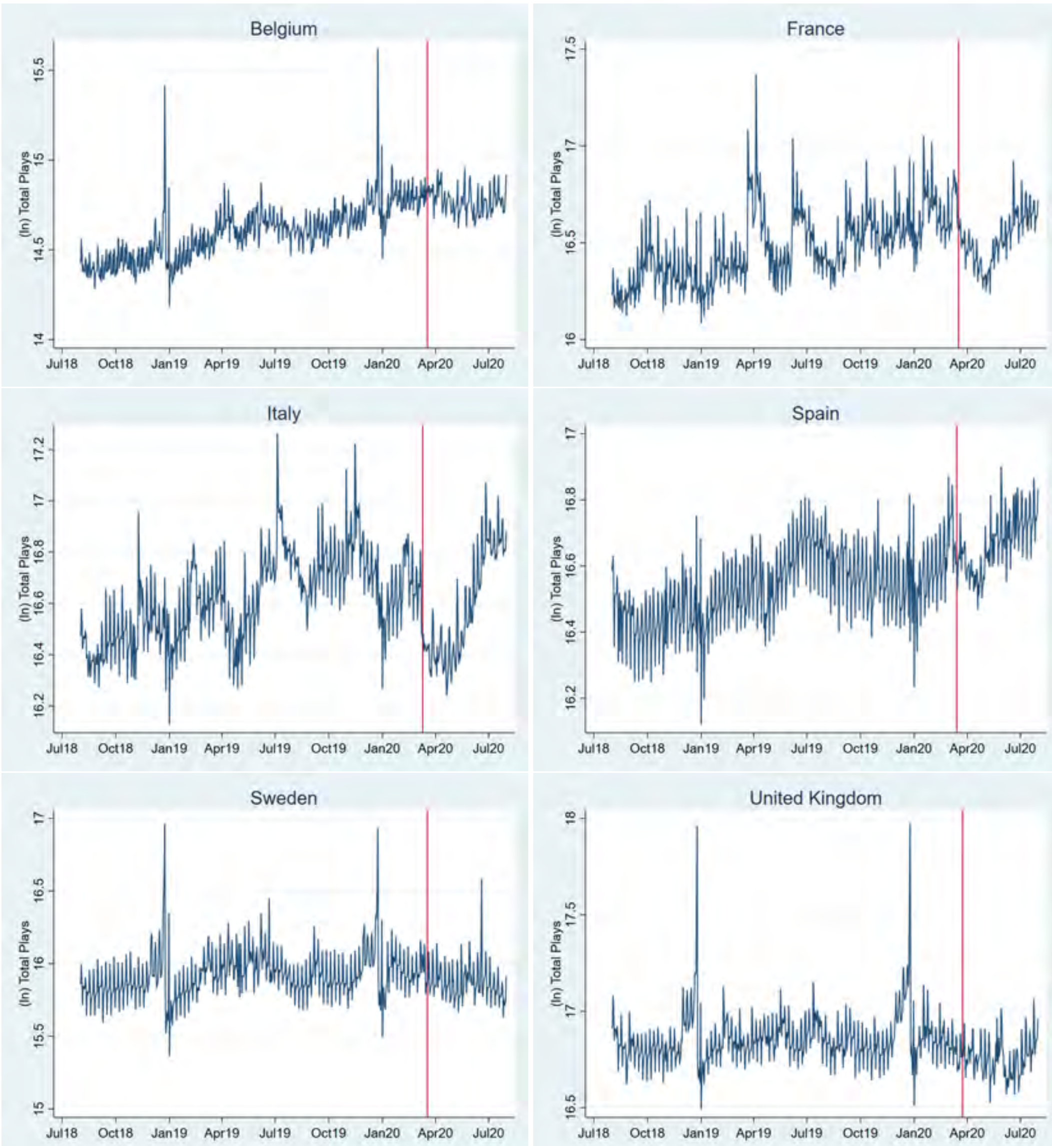
Figure 4: Daily (ln) Total Numbers of Plays, August 2018 - July 2020



employs equal-weighted 7-day moving average to measure daily COVID infection because it gives a better measure of how people perceive the pandemic and also corrects the reporting bias of weekends, holidays and some exceptional negative values (ex-post adjustments). The aim of the regression is to check if the lockdown causes the time trend to change its direction and check if on top of the trend component COVID infection provides additional explanatory power.

To validate the result, this work proposes the following checks. First, we conduct 10-fold cross-validations to compare five different specifications (Zhang and Yang, 2015). Next, we check if the break of the slope of the trend at the first lockdown day could be defended as the true structural break. Point estimates and confidence intervals of the change in slope at 21 different supposed break points are compared side-by-side. The final check is a placebo test that imposes a hypothetical pandemic on the same period in 2019. The aim is to verify if the sharp change of trend at the break date is not merely an annual pattern. A no-result is thus a piece of evidence supporting that the pandemic indeed changed individuals' nostalgia consumption preference.

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3.2 Logistic Regression

The empirical analysis relies on a logistic regression with standard errors clustered in days. The model employs a difference-in-difference approach where lockdown is considered as a treatment and the period since the lockdown is the treated sample. The main focus of the analysis is whether lockdown led to a change in nostalgia consumption preference revealed by changes in constant and slope. Denote the probability of an event $Y = 1$ (a nostalgia song being played) by p. The log-odds is thus:

$$\text{logit}(p) = ln\Big(\frac{p}{1-p}\Big)$$

We assume that the log-odds of $Y = 1$ is explained by a set of explanatory variables that includes a lockdown indicator and its interaction with a quadratic trend and 7-day moving-average of COVID incidence rate. The time variable t is centered at the first lockdown day. The log-odds is modelled as the following:

$$\begin{aligned}\text{logit}(p) &= \alpha_1 + \alpha_2 Lockdown_t + \beta_1 t + \beta_2 t^2 \\ &= +\beta_3 Lockdown_t t + \beta_4 Lockdown_t t^2 + \beta_5 COVID_t + \boldsymbol{x'}\gamma \end{aligned} \tag{1}$$

where the vector $\boldsymbol{x}$ includes the number of newly released songs, the log of total plays of the day, the average nostalgia level of the same day of 2019, the day of the week (Monday, Tuesday and so on), and five relatively more distinctive track features (acousticness, danceability, energy, liveness and valence). The inclusion of track features controls for the music trend of the day. For instance, users may have a preference of more acoustic music to other genres and they might only find the desired mood in old songs.

The logistic regression maximizes the following log-likelihood function:

$$l(\boldsymbol{\beta}) = \sum_{i}^{N} \Big[Y_i ln(p_i) + (1 - Y_i) ln(1 - p_i) \Big]$$

This research proposes the following hypotheses:

1. $\beta_3 > 0$. Lockdown sharply increased the slope.
2. $\beta_1 + \beta_3 \geq 0$ and $\beta_2 + \beta_4 \leq 0$. Nostalgia consumption increased in the beginning of the lockdown and fell when time went on.
3. $\beta_5 \geq 0$. Higher incidence rate induces more nostalgia consumption.

Hypotheses 2 and 3 may be valid simultaneously but may instead exclude one another. Lockdown period covers the days of severe infection, and thus two hypotheses may compete for significance.

Table 2 reports the coefficients of selected variables of the regression results of the six countries. Nostalgia consumption followed a general downward trend before the lockdown in all countries except the UK. A significant β_3 implies that the trend took a sharp turn at the lockdown implementation. Overall, we find support of Hypothesis 1. To better illustrate the evidence, Figure 5 shows the prediction of nostalgia consumption against numbers of days after lockdown. No incremental increase in nostalgia consumption right in the beginning of the lockdown, but it gradually rises and then falls towards the end of the sample period, consistent with Hypothesis 2. The peak is found roughly 80-100 days after the first day of the lockdown, coinciding roughly with the intermediate phase of relaxation in June. It also shows a stark difference from the counterfactual supposing that nostalgia consumption has followed the pre-lockdown trend. The UK actually exhibits a similar pattern. The relatively flat in-lockdown trend is a result of the impreciseness of the pre-lockdown trend that diminishes the scale. Besides, we find no evidence supporting an upward adjustment of the constant term (α_2), except in Spain.

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Table 2: Logit Regression: Baseline Results

	(1) BE	(2) FR	(3) IT	(4) ES	(5) SE	(6) UK
Pre-Lockdown						
time (β_1)	-0.0060	-0.1234***	-0.0162	-0.0267***	-0.0673***	0.0013
	(0.0048)	(0.0158)	(0.0182)	(0.0086)	(0.0195)	(0.0063)
time-sq (β_2)	-0.0001*	-0.0011***	-0.0002	-0.0004***	-0.0007**	0.00005
	(0.00006)	(0.0002)	(0.0002)	(0.0001)	(0.0003)	(0.0007)
in-Lockdown						
time (β_3)	0.0218***	0.1850***	0.0568***	0.0495***	0.0925***	0.0101*
	(0.0055)	(0.0211)	(0.0002)	(0.0140)	(0.0187)	(0.0055)
time-sq (β_4)	0.00001	0.0008***	-0.00001	0.0003***	0.0006**	-0.0001
	(0.00006)	(0.0002)	(0.0002)	(0.00009)	(0.0003)	(0.00009)
$\beta_1 + \beta_3$	0.0158***	0.0616***	0.0406***	0.0228***	0.0252***	0.0114***
$\beta_2 + \beta_4$	-0.0009***	-0.0003***	-0.0002***	-0.0001***	-0.0001**	-0.00006**
Lockdown	-0.0215	0.8815	-0.0981	0.7508**	-0.3358	-0.0290
	(0.0959)	(0.6066)	(0.3662)	(0.3612)	(0.3444)	(0.0980)
COVID	-0.0219	0.1154	-0.0110	-0.0018	0.4111***	0.0788*
	(0.0228)	(0.1313)	(0.1026)	(0.0749)	(0.1001)	(0.0437)
Total plays	0.2128*	-2.0539***	-0.7494*	-0.7303	3.097***	0.2078
	(0.4433)	(0.3749)	(0.3954)	(0.7209)	(0.4337)*	(0.4304)
New tracks	-0.0163***	-0.0125**	-0.0197***	-0.0149***	-0.0269****	-0.0173***
	(0.0017)	(0.0032)	(0.0044)	(0.0749)	(0.0032)	(0.0029)
Nostalgia 2019	4.262**	20.84***	-2.929	17.42	3.327***	1.031
	(1.970)	(2.730)	(8.400)	(11.76)	(0.9605)	(1.140)
Weekday FE	Yes	Yes	Yes	Yes	Yes	Yes
Track features	Yes	Yes	Yes	Yes	Yes	Yes
N	554123431	3373610349	3504103652	3588106348	1713501823	4166040525
Pseudo R2	0.1380	0.1305	0.0852	0.0722	0.2473	0.2068
log-likelihood	-94216643	-1.363e+08	-1.739e+08	-2.315e+08	-1.819e+08	-8.551e+08

Standard errors clustered in days in parentheses * $p < .1$, ** $p < .05$, *** $p < .01$

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As any significant (and insignificant) results could be driven by outliners, Figure 6 plots daily average values of residuals of a model that excludes the time trend and COVID indicence rate against time. The distribution of residuals across time shows what would be explained by the excluded time component and COVID. Roughly speaking, those residuals follow a downward trend before the lockdown and an upward trend after the lockdown, consistent with Hypothesis 2. Figure 7 zooms to the period between 1 February to 31 May to verify if the slope took a sharp change at around the lockdown date. While the case of Spain is unclear, other five countries tend to show some upward shift in slope.

COVID incidence rate is insignificant for Belgium, France, Italy and Spain in the baseline regressions. Its impact may well be absorbed by the change in trend due to the lockdown.[10] In Sweden where no hard lockdown has been imposed, COVID incidence rate is highly significant. One percentage point increase in the incidence rate is associated with an increase in the odds of nostalgia consumption by a factor of 1.5. Note that even Sweden had no tight lockdown measures, it was reported that mobility had decreased significantly within Sweden.[11] Despite that, further checks are necessary before pinning down the effect on nostalgia consumption of music.

Total number of plays are positive and significant in Belgium and Sweden, while negative and significant in France and Italy. These mixed evidence give no answer to the expectation that newly-joined users, may be drawn to Spotify due to the lockdown, tend to listen to older songs.

As shown in Figure 8, the peak of COVID incidence rate predates the peak of nostalgia consumption, except in Sweden. Lockdown broke the trend but the effect became full-blown after the peak had passed. Evidence so far suggest that users tend to react to the lockdown only gradually but COVID incidence fails to explain the rise and fall of nostalgia consumption. This conclusion is intuitive as people may not pay attention to the ups and downs of incidence rate while lockdown is a drastic, encompassing and exceptional measure that produced a lasting effect regardless the incidence rate.

[10] Regressions (not shown) removing any trend components show that COVID incidence rate is positive and significant for all six countries.

[11] http://press.telia.se/pressreleases/svenskarna-stannar-hemma-under-paasklovet-2990179

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Figure 5: Prediction of Nostalgia Consumption with 95% CI: Illustrating Changes in Slope before and after Lockdown

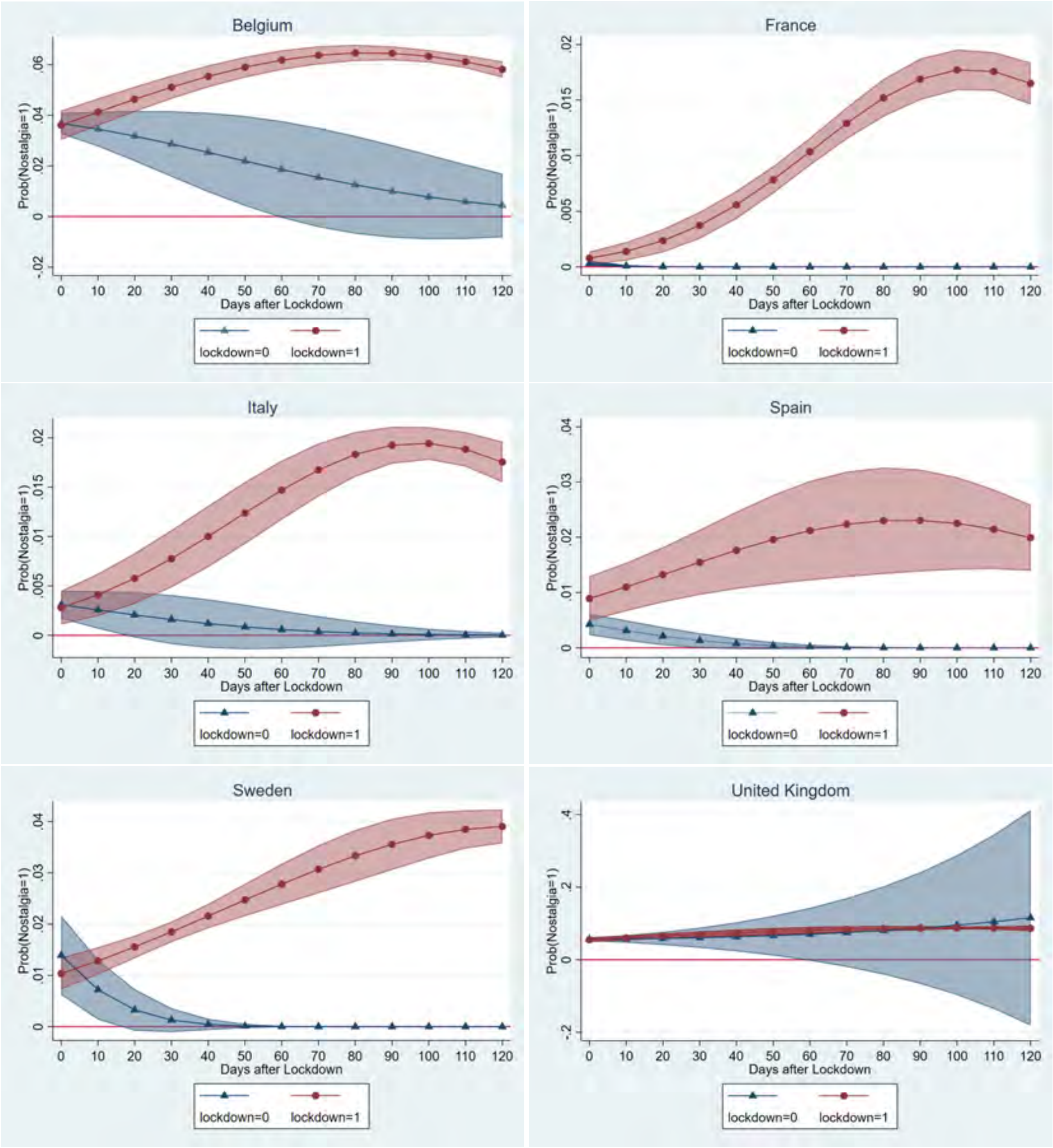

Figure 6: Residual Plots: Illustrating Nostalgia Level over time

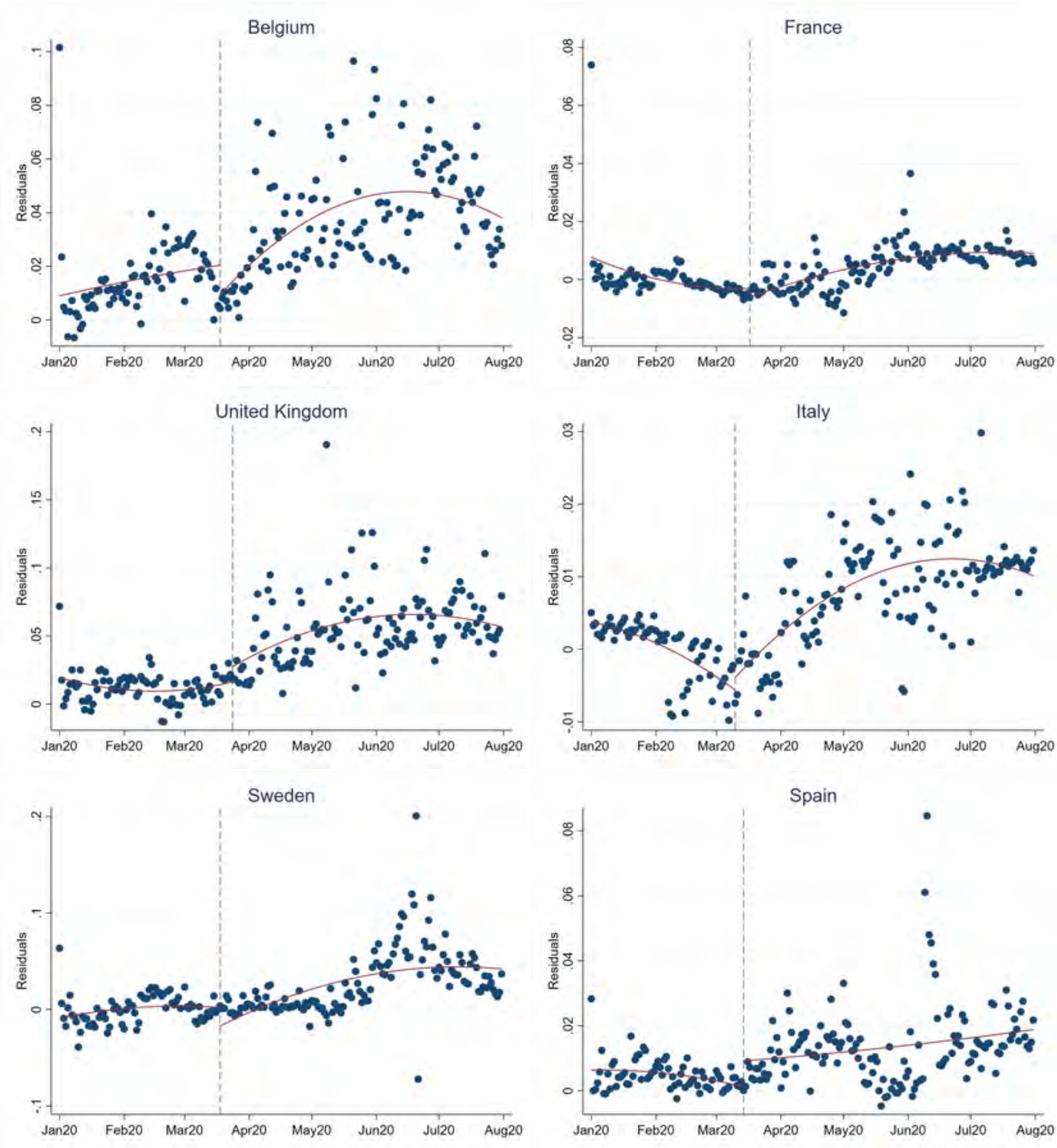

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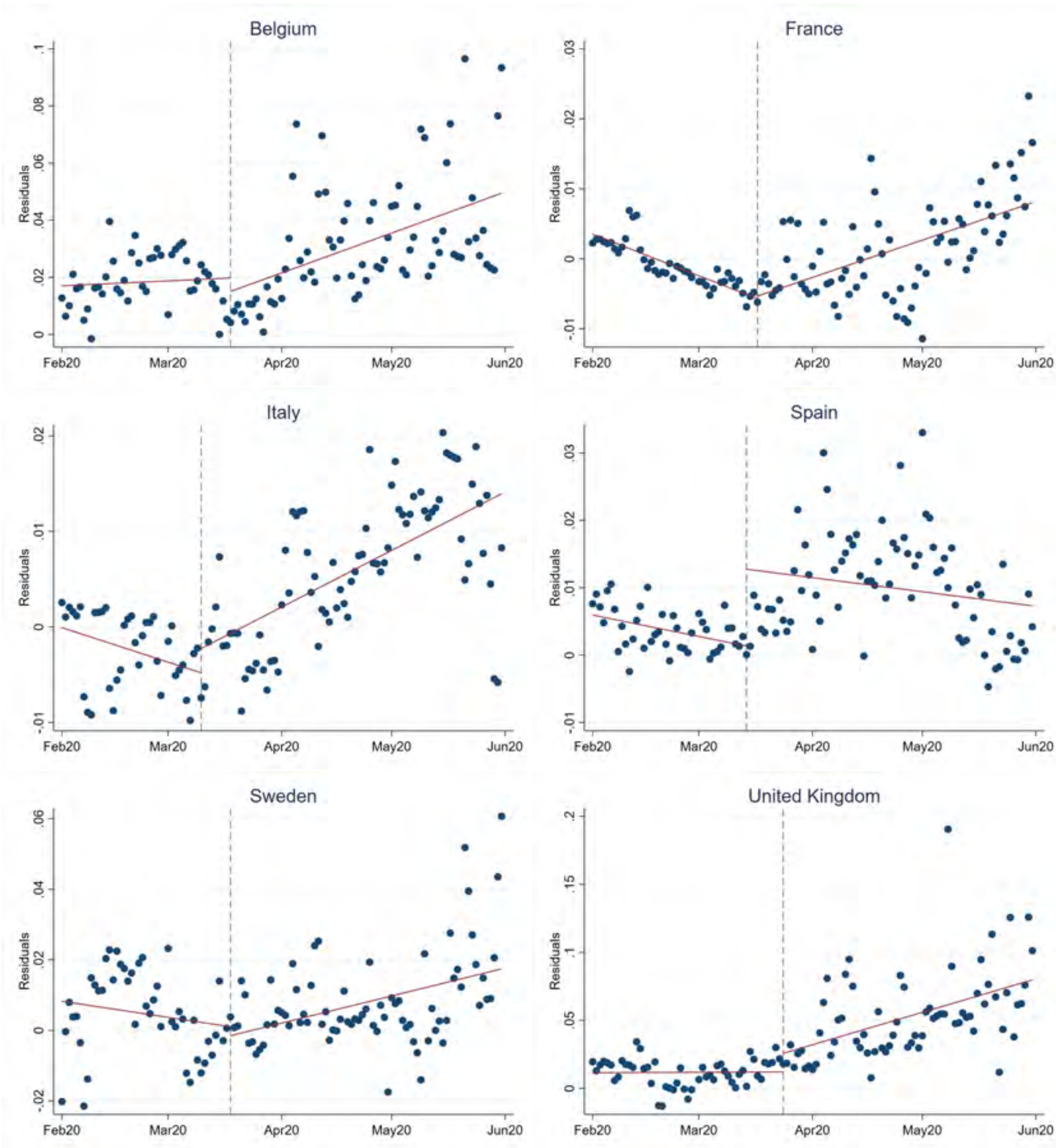
Figure 7: Zoomed Residual Plots: Illustrating Nostalgia Level over time



3.3 Lockdown and COVID Infection: Which one is more shocking?

The baseline regressions show that COVID incidence rate is not a robust and significant factor in explaining nostalgia consumption, given a quadratic trend is modelled. This result seems to suggest that users react to the lockdown but less so to the actual COVID infection figures. How-

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ever, as mentioned, these two factors are certainly competing for significance as both of them measure two different dimensions of the pandemic. Readers may have already noticed that the COVID-19 pandemic appears coinciding the trend of the nostalgia consumption with a delayed peak of the latter. While the baseline model assumes a linear relationship between COVID incidence rate and the log-odds as Equation (1) indicates, this section attempts to explore any non-linear effects of COVID. People might have been negligent when the pandemic first hit the country but then shocked by the incapacity of hospitals to cope with patients. When time went on, people got used to the shock and reverted back to their normal consumption preference. As a result, the effect of COVID incidence is non-linear in time. This hypothesis suggests that people do react to current COVID infection level but such an effect depends on time, perhaps producing an inverted-U shaped curve of nostalgia consumption during the lockdown, as shown by Figure 8.

To test this hypothesis, we modify the logistic regression model by dropping lockdown but interacting the (natural log of) COVID incidence rate with the quadratic trend. The idea is to allow the effect of COVID infection to be non-linear over the time dimension. Instead of reporting a table full of numbers, we plot in Figure 9 the average marginal effects of COVID against days since the first time COVID incidence rate exceeds 1. The effect of COVID infection is very small in the beginning and it increases gradually and becomes significant in France, Italy, Sweden and the UK roughly around 50 days after the first time COVID incidence rate exceeds 1 (Mid-Late April) that corresponds to the time when the peak just passed. However, the effect is insignificant in Italy and Spain while the estimated variance in the UK becomes very large after 75 days. In short, COVID infection could explain some variations of nostalgia consumption but is limited to some countries and to a short window of time. Take France as an example. At the peak, a one percentage change in incidence rate is associated with 0.75% increase in the probability of playing a nostalgic song.

The result points to the statistical limitation that the in-lockdown quadratic trend may actually cover up the influence of COVID infection on nostalgia consumption. Although the baseline result suggests that COVID fluctuations around the trend does not improve explanation, it does not mean people do not react to it. A mood or an emotional state of a person may be triggered by recent events, but could be persistent for some time and do not recover

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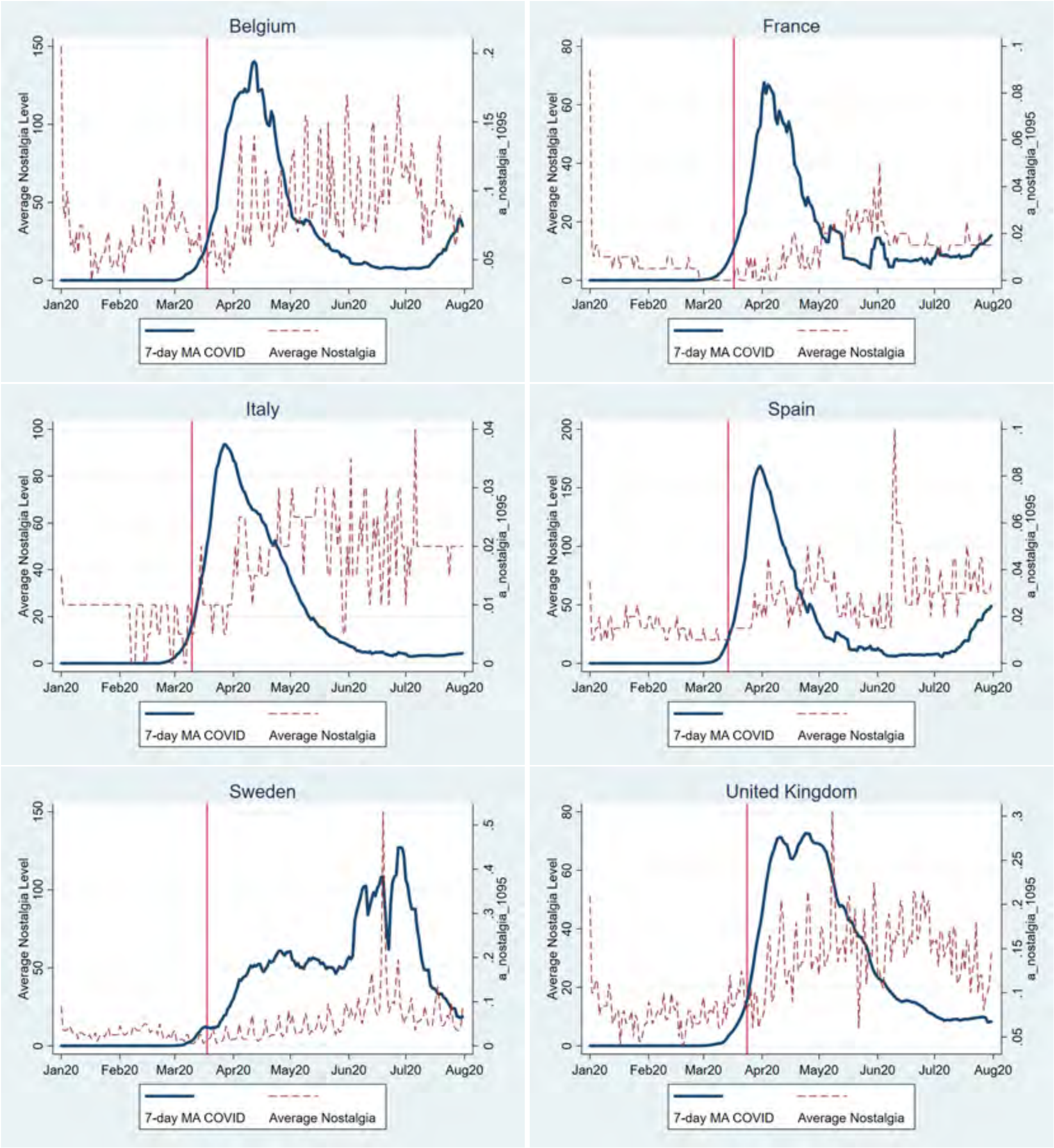
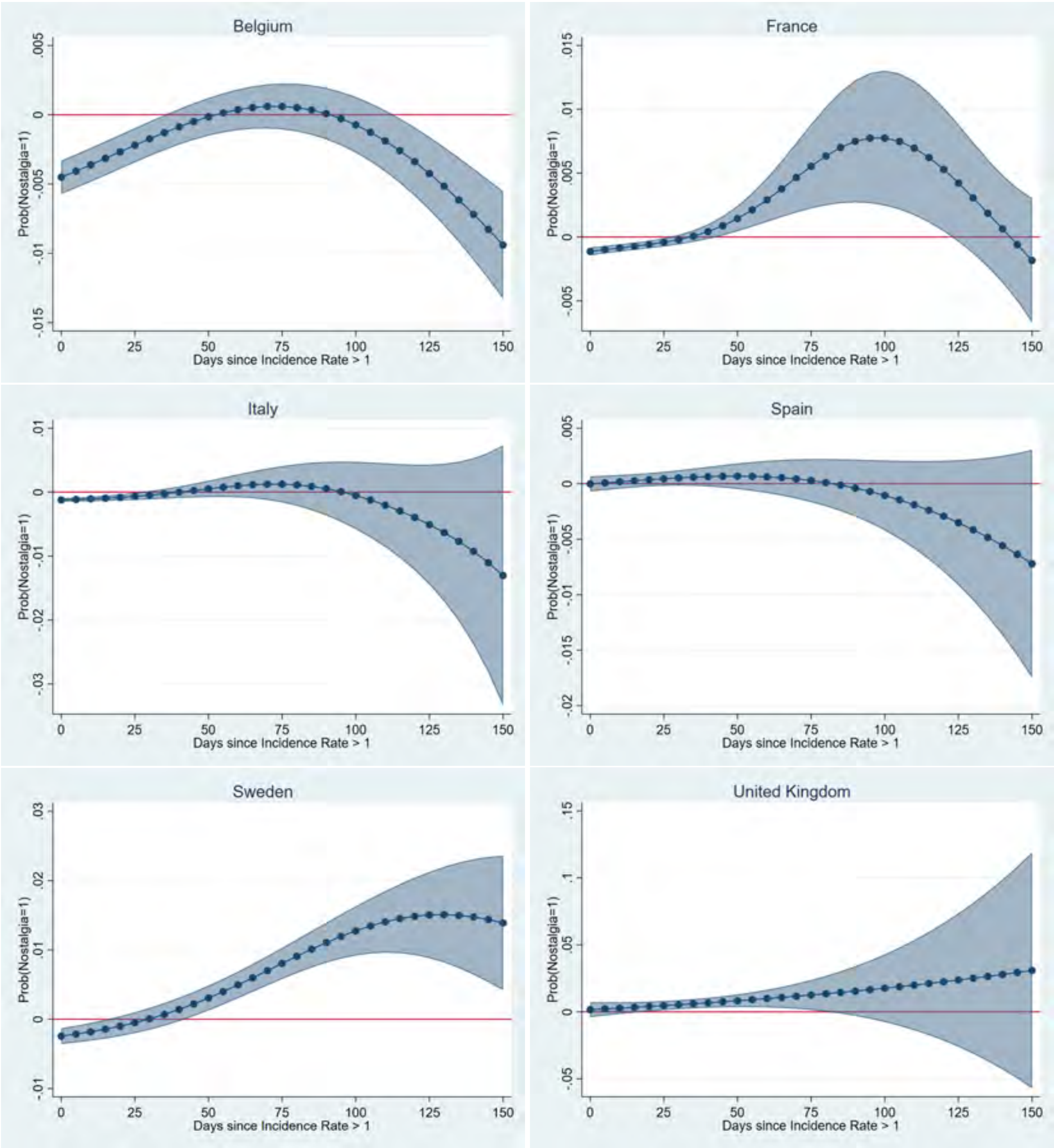
Figure 8: COVID Incidence Rate and Nostalgia Consumption



quickly. It is thus difficult to model any impact of COVID infection on nostalgia consumption and thus not surprising to see COVID infection not satisfactorily significant in the explaining nostalgia consumption.

Figure 9: The Average Marginal Effect of COVID Incidence on Nostalgia Consumption



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3.4 Robustness Check 1: 10-fold Cross Validation

Evidence so far do not draw any conclusion concerning the model's explanatory power. This section performs k-fold cross validations to choose the best model for each country (Zhang and Yang, 2015). In brief, k-fold cross-validation randomly divides a sample into k folds of equal size and fits the model on $k - 1$ folds while taking the remaining fold as a validation

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set. As a result, we conduct k tests and select the best model among a set of models based on minimizing root-mean-square error (RMSE). Despite being increasingly challenged, we take $k = 10$ as most researchers advise (Arlot and Celisse, 2010). As each draw is random, each k-fold cross-validation may generate different results. To strive for a more convincing answer, ten times of 10-fold cross-validation are done to compare the following five different models:

1. Baseline (Lockdown interact with distinct quadratic trend pre- and in-lockdown, COVID)
2. No lockdown; COVID interacted with a quadratice trend
3. No lockdown; COVID, one single quadratic trend over the whole period
4. Lockdown interact with distinct quadratic trend pre- and in-lockdown; No COVID
5. No lockdown; No COVID; a single quadratic trend over the whole period

We have already shown some results of the first two models. Model 3 contains one single quadratice trend over the whole period while COVID enters the model independently. Model 4 excludes COVID from the baseline and Model 5 contains no pandemic-related information at all. All regressions utilize all observations from January to July 2020 and the predicted values are compared against the actual values. Table 3 reports the average root mean square errors (RMSE) of the ten times of 10-fold cross-validation and also the improvement in percentage of the best model over Model 5.[12]

Table 3: Robustness Check: 10-fold Cross-Validation

Model	(1)	(2)	(3)	(4)	(5)	Improvement
BE	0.25862247	0.27784696	0.27298335	*0.25861679*	0.27152588	-4.75%
FR	0.10781144	0.75119275	0.28095738	*0.10773338*	0.54211443	-80.13%
IT	0.12295221	0.12290002	0.1229657	*0.12288158*	0.12966048	-5.23 %
ES	*0.15394131*	0.17979503	0.16019589	0.15397355	0.16018556	-3.90%
SE	*0.19897844*	0.20008971	0.2005303	0.19912872	0.25823649	-22.95%
UK	*0.29446747*	0.29535151	0.29534308	0.2944894	0.3406044	-13.55%

Note: The smallest values are highlighted in italics.

The baseline model performs the best for three countries (Spain, Sweden and the UK) and Model 4 (Baseline without COVID) edges over the baseline for other three countries (Belgium,

[12] Each 10-fold cross-validation produces 10 RMSE. Running 10 times 10-fold cross-validation implies in total 100 RMSE are generated. We only report the average value of the 100 RMSE.

France and Italy). Breaking the trend at the first lockdown day always dominates those without. For those COVID provides additional explantory power, two of them (Sweden and the UK) are positive and significant, as shown in Table 2. Take Sweden as an example, a percentage point increase in the incidence rate is associated with an increase in the odds of nostalgia consumption by a factor of 1.5. Such a significant substantial impact coincides with the fact that Sweden has had no tight lockdown, though it is speculative to conclude that the rather lax policy shifted the source of impact on nostalgia consumption from lockdown to COVID infection.

3.5 Robustness Check 2: When was the actual break?

Readers may question if the lockdown date (the structural break) simply coincided with some reversion of trend and thus the presented results only reflect some natural process that would also have happened without the pandemic. To answer to this challenge, we re-run the baseline regression with 20 other hypothetical break dates, ranging from 10 days before to 10 days after the actual first lockdown day. Figure 10 reports the point estimate and the 95% confidence intervals of β_3, which refers to the change in slope at the corresponding break point.[13] Belgium is the best example, where the peak is exactly at the actual first lockdown day and the confidence intervals expand going into later dates. France is similar but the peak is found at $t^L + 1$. As users' reaction may lag behind the policy implementation, it should be regarded as a consistent result as long as the peak is found not far from t^L . The case of Italy is interesting. The point estimate peaks locally at $t^L - 2$, when the Italian government quarantined the whole Lombardy and 14 other provinces on 8 March, but then the estimate soars since $t^L + 4$. Sweden peaks locally at $t^L + 3$ and the subsequent increases in the point estimate are very small for $t > t^L + 4$. In any case, it is quite difficult to pin down the structural break date as Sweden has not tightly locked down the nation. The UK case is complex. While we reject the actual break happened after t^L as the confidence intervals expand sharply, it is difficult to pin down the actual break date. Note that the magnitude is relatively small compared to other countries and that the UK is the last to lock down its nation (except Sweden). Users in the UK might have already reacted to the pandemic, limiting mobility, storing food, and avoiding seeing each other without the government's advices and orders. Generally speaking, the break check provides additional evidence that nostalgia consumption experienced a structural break around the actual first

[13]The pre-lockdown slope is $\beta_1 + \beta_2 \times t$ and the in-lockdown slope is $\beta_1 + \beta_3 + \left(\beta_2 + \beta_4\right) \times t$. The difference is thus β_3 and the quadratic term is irrelevant at the break as we have centered the trend values at the break point.

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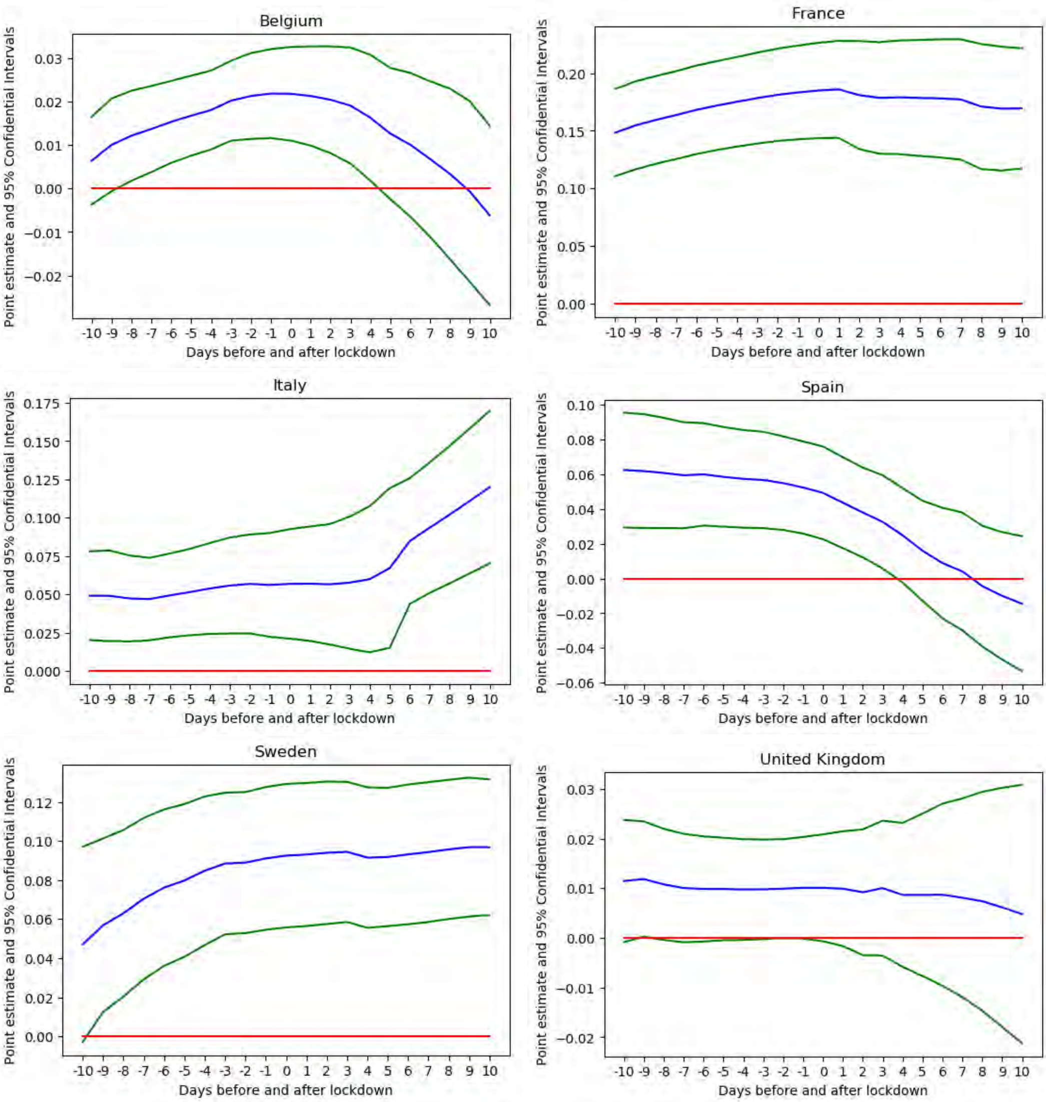
lockdown day. Spain presents a quite different picture and the graph basically reject that the actual break date does not predate the first lockdown day. Judged with evidence such as the residual plot of Figure 6, Spain exhibits a distinctive pattern from other five countries .

Figure 10: The Effect of Lockdown on the Trend with Different Break Points



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3.6 Robustness Check 3: Placebo Test

Despite the previous robustness check, readers may doubt if the change in trend is in fact an annual pattern but not due to the lockdown. It is possible for some reason nostalgia consumption takes a sharp turn and goes up every year in March and then fall towards to summer.[14] This section attempts to explain nostalgia consumption of the period January-July 2019 by the lockdown and COVID data of the 2020 (the baseline specification) matched to the same day of 2019. Again, we check if the slope changes sharply at the break. A no-result of this placebo test is thus a strong evidence supporting that the lockdown is actually a factor driving nostalgia consumption in 2020. Figure 11 reports the point estimate and also the confidence intervals of β_3. For Belgium, its largest estimate comes on $t^L - 1$ but is negative, meaning that the slope turns sharply downward after the break. France peaks at roughly $t^L + 5$. Italy sees all estimates below zero, whereas Sweden peaks at $t^L - 2$. Finally, there is no clear answer to where is the break for Spain and the UK.

No country reproduces a similar pattern, implying that nostalgia consumption during the 21-day period does not exhibit an annual pattern. While most of the point estimates stay above zero in Figure 10, meaning that the trend turned upward in March 2020, the pattern in 2019 is mixed with Belgium, Italy and the UK staying below zero for a large range of hypothetical break dates. Generally speaking, the placebo test rejects the claim that the break in slope is a reflection of an annual pattern, and thus provides substantial support to Hypothesis 1.

Table 4 summarizes the results of sections above. Baseline regression result shows that the lockdown treatment breaks the trend of nostalgia consumption and the change in slope is positive and significant for all six countries. The significant and negative quadratic trend term suggests that the upward shift in slope caused by the lockdown diminishes over time, while the residual plot suggests that the pattern of Spain may be driven by outliners. COVID improves the model's explanatory power and is significant for Sweden and the UK only. By comparing the baseline model using the first lockdown date as the actual break data with 20 other hypothetical break dates, we find strong support for the hypothesis that the sharp change in slope happened at or around the first national lockdown date (or national travel advice announcement date for

[14] The baseline regression has included the daily average nostalgia level of 2019, which should have adequately taken care of this concern.

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Sweden) for Belgium, France and Sweden. The placebo test shows that no country experienced a similar slope break in 2019.

Figure 11: Placebo Test: The Effect of a Counterfactual Lockdown on the Trend with Different Break Points in 2019

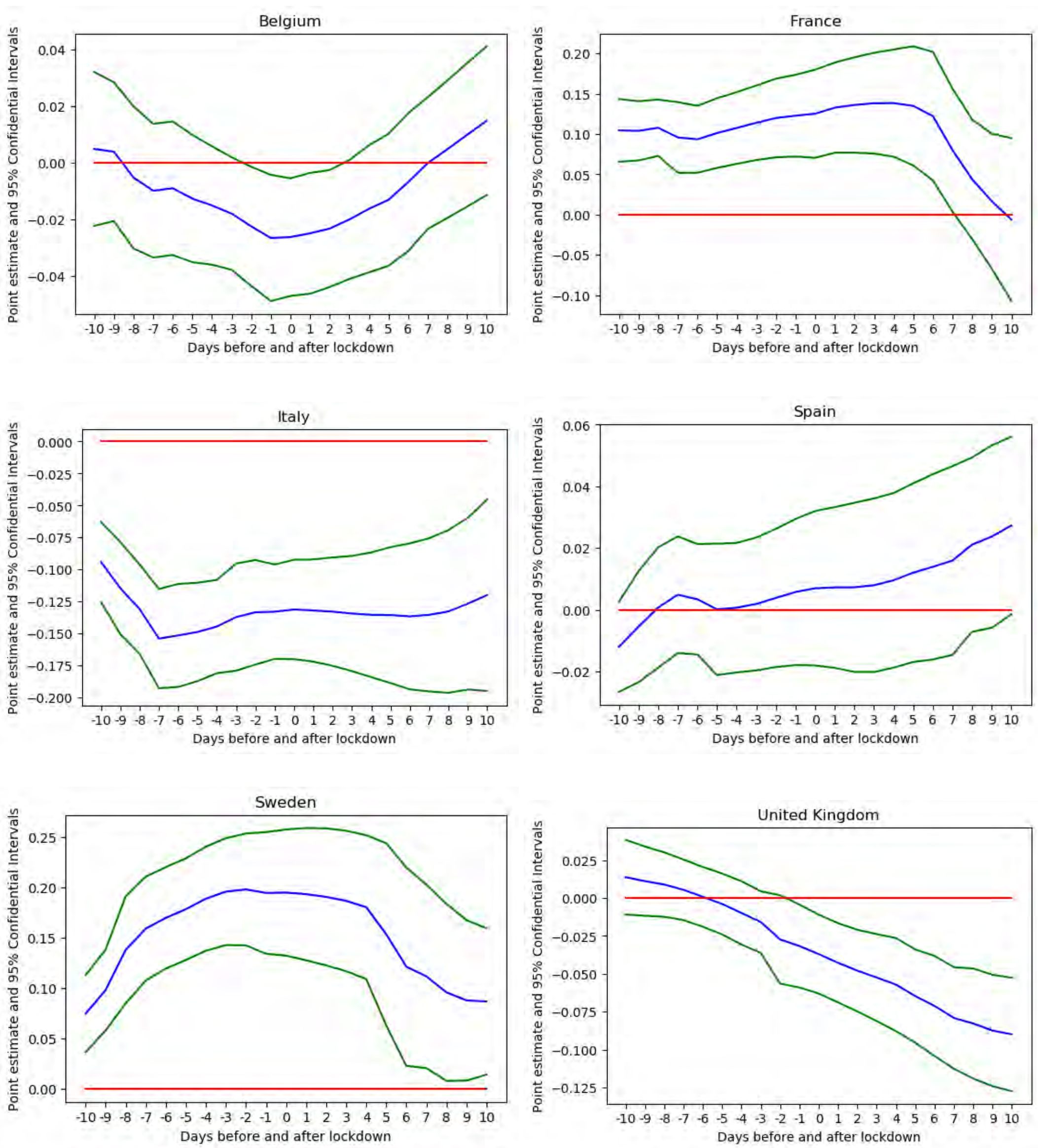

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Table 4: Summary of Results

	BE	FR	IT	ES	SE	UK
Trend turns upward at lockdown	✓	✓	✓	✓	✓	✓
Quadratic Impact of Lockdown	✓	✓	✓	×	✓	✓
COVID improves explanation while significant	×	×	×	×	✓	✓
Support of Break at Lockdown	✓	✓	unclear	×	✓	unclear
Support of Annual Pattern	×	×	×	×	×	×

4 Discussion and Conclusion

By scraping Spotify's, the popular online music streaming platform, public data covering almost 17 trillion of plays in six countries, this research provides some evidence of increasing nostalgia consumption of music caused by the pandemic. While Spotify users respond to the lockdown that significantly breaks the trend, COVID incidence rate is a less significant factor. The difference could be explained by the old tale of substance or style. People with limited attention capacity could only pay attention to the more obvious information. It is arguably true that a lockdown gave a stronger signal of severity than the actual COVID incidence rate. A more convincing explanation is that the lockdown itself not only signaled a negative outlook but also caused significant psychological impacts even when the current incidence rate is low. The lockdown during the pandemic involved many exceptional orders that limit individuals' liberty and affect employment and usual social interactions. These changes might have caused ill emotions and people dived into nostalgic music to escape the reality even if the virus had not caused their or their close relatives' health any harms. Demand for nostalgia grew with frustration as the lockdown remained in place and such a change in behavior was gradual but did not react closely to the change of the severity of the pandemic.

The literature provides abundant evidence of impacts of the COVID-19 pandemic on mental health (Cao et al., 2020; Pfefferbaum and North, 2020; Qiu et al., 2020; Rajkumar, 2020; Odriozola-González et al., 2020; Mucci et al., 2020, and many others). Brooks et al. (2020) identified five stressors during a lockdown, namely, duration of lockdown, fears of infection, frustration and boredom, inadequate supplies, and inadequate information. Psychological impacts of the pandemic may easily translate into change in consumption behaviors as rational individuals seek remedies to counter any adverse psychological distress. A potential cure is to acquire nostalgia and a relatively cheap channel to achieve this goal is to listen to music of the

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"good old days". The relationship of a time of difficulty and nostalgia consumption has been discussed in recent research (Weed, 2020; Gammon and Ramshaw, 2020), while previous work supports that nostalgia induces more positive affects than negative ones (Cheung et al., 2017; Hussain and Alhabash, 2020).

The exceptional orders in this exceptional time have led people to seek nostalgia for pleasure. The current work attempts to identify the more significant factor in determining nostalgia consumption between the lockdown and the infection and concludes that lockdown changes sharply the trend of nostalgia consumption and COVID incidence rate contributes little to the explantory power of the model. This work also shows that the lockdown effect is non-linear as the lockdown nostalgia impact eventually faded away. Although future data are not yet available, the author speculates that the incentive for seeking nostalgia would be much weaker during a second-wave or a second restrictive lockdown.

The result is not only relevant for music producers and music lovers but also for the general public and the policy-makers to better understand individuals' possible responses to crises. Music consumption is a result of personal utility maximization. Users of the streaming platform (no marginal monetary cost of additional consumption) choose whatever they like based on their preferences and moods and implicitly they believe the music they choose pleases them (generates higher utility). If old songs make them feel better, it may be because those song counter some sad emotions during the very special period. Care centres, hospitals, stores and any places where music could be played publicly should consider the positive effects of playing nostalgic music as a response of the adverse effects of the pandemic.

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Short-term Labour Market Effects of COVID-19 and the Associated National Lockdown in Australia: Evidence from Longitudinal Labour Force Survey

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We examine the short-term labour market effects of COVID-19 and the associated national lockdown in Australia by estimating person-fixed-effects models using the Longitudinal Labour Force Survey. COVID-19 decreased labour force participation (LFP) by 2.1%, increased unemployment by 1.1% and reduced weekly working hours by 1.1. The national lockdown decreased LFP by 3.3%, increased unemployment by 1.7%, and decreased weekly working hours by 2.5. The probability of working on Fridays decreased by 10% while working fewer hours due to being on leave, work shifts, not having enough work and losing jobs all increased due to the lockdown. The pandemic and the lockdown increased underemployment and job search efforts significantly. In terms of heterogeneity of these effects, our analysis shows that those with up to high-school education experienced larger reductions in their LFP and working hours than others. However, immigrants and individuals with shorter job tenure or occupations unsuitable for remote work were hit the hardest in terms of unemployment.

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1. Introduction

COVID-19 is one of the greatest plagues of the 21st century. The World Health Organisation (WHO) declared it a global pandemic on March 11, 2020. Approximately 19 million cases have been reported and 716,000 people have died worldwide as of 8 August 2020 (WHO, 2020), and countries have implemented various policies for fighting the virus. For instance, the government of New Zealand implemented one of the strictest lockdowns in the world, only permitting people to leave their homes for essential reasons like buying food and going to the doctor. This followed the closure of New Zealand's borders to non-nationals. Sweden, on the other hand, did not impose a national lockdown at all, but trusted people to socially distance themselves. U.S. stay-at-home orders lasted for several weeks for implementing states, while some states never issued such orders. Along the lines of New Zealand's approach, the Australian government enacted a national lockdown on March 21st, ten days after the WHO declaration. The purpose of the lockdown was to suppress the virus and reduce the number of infected people, to ensure that Australia's health system would be able to treat the patients who required hospitalisation.

The national lockdown was enforced with "Stage 3" restrictions in all states at the same time, as follows. A person could leave his/her house for only four reasons (grocery shopping, medical care, daily exercise and going to work), no one could have visitors at home, and everyone must maintain a distance of 1.5 metres from others in public places. Moreover, all non-essential services were shut down as a result of the social distancing rules[1]. The Australian government provided a job-keeper payment program, which was announced on March 30th, to counteract the negative economic consequences of these policies for the labour market. Eligible businesses that had suffered significant loss (about 30%-50% of GST turnover) were entitled to a fortnightly payment of 1500 AUD for each eligible employee[2]. Moreover, a 550 AUD

[1] Pubs, bars and nightclubs, as well as all entertainment and cultural venues, were closed, while restaurants, cafes and bottle shops were take-away only. Beauty services were also closed, but hairdressers remained open. Only shopping centres, markets and other retail shops selling essentials were still allowed to trade, and these were subject to the social distancing rules.

[2] A business is not eligible for a job-keeper payment if the entity is an Australian government agency or a local governing body, is owned by an Australian government agency or local governing body or is a sovereign entity or owned by one. Moreover, companies that have entered bankruptcy or are in liquidation are not eligible.

boost to fortnightly welfare payments for the unemployed was announced at the same time, to provide further financial support to job-seekers[3]. In addition, schools provided online education but were physically accessible only for students whose parents were essential workers, while all families in Australia were provided with free childcare from April 6th, 2020. Although the government tried to mitigate the adverse effects of the pandemic and the lockdown on the labour market, there is no doubt that the closure of many businesses has resulted in severe job losses and increased unemployment. Overall, the pandemic and the associated national lockdown have resulted in the country's first recession since 1991, while its GDP decreased by 0.3%.

To the best of our knowledge, this is the first paper in the literature to examine the short-term labor market effects of the pandemic and the associated national lockdown in Australia. We use the Longitudinal Labour Force Survey (LLFS) data that is accessed by the authors through a secure DataLab at the Australian Bureau of Statistics (ABS). This dataset, similar to the U.S. Current Population Survey (CPS), is a monthly rotating panel where each respondent is interviewed eight times consecutively (once per month) and new respondents are added to the survey each month. This paper uses the dataset that includes interviews until the end of May 2020 and includes variables such as labour force participation (LFP), unemployment and working hours, and whether or not the respondent worked on each day in the reference week, along with information on the state, year and month of interview. The questions about the labour market conditions are asked with respect to the previous week (Monday-Sunday), a period which we refer to as the "reference week". Our dataset includes information on the exact starting and finishing *dates* of the reference week. Using this information, we define whether a person is surveyed before or after the WHO pandemic declaration date and the national lockdown date, which are labelled 'COVID-19' and 'national lockdown' hereafter. Our baseline regression sample includes everyone aged 15 to 70 who was surveyed between 1 January 2019 and 30 May 2020, and consists of around 280,000 observations. Importantly, the national lockdown continued in all states until 12 June 2020, when restrictions started to ease across the country.

[3]A person must be between 22 and 70, an Australian permanent resident or citizen, unemployed and either looking for a job or sick and unable to work in order to be eligible to receive the job-seeker payment.

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Therefore, everyone in our regression sample was exposed to stage three lockdown policies from the time they were implemented until the end of the regression period. We estimate the effects of COVID-19 and the associated national lockdown on labour market outcomes using person fixed effects, controlling for a rich set of covariates. Thus, our identification depends on within-person variations over time and controls for person-specific factors such as psychological variables. Importantly, labour force surveys generally do not ask about work characteristics if a person is unemployed or out of the labour force. Fortunately, the longitudinal nature of our data enables us to measure people's work characteristics before the pandemic/lockdown if they were working before the pandemic but ended up unemployed or out of the labor force during the pandemic period. Accordingly, we can investigate interaction effects of the COVID-19/national lockdown with individuals' demographic and work characteristics, which has important implications for public policy and income inequality in the Australian population.

Our results show that COVID-19 led to a 2.1% (or 2.8% at the mean) decrease in the LFP, a 1.1% (or 24% at the mean) increase in the unemployment, a 4% decrease (or 7.8% at the mean) in the full-time employment and a 1-hour decrease in weekly working hours. Moreover, the national lockdown decreased the LFP by 3.2% (or 4.3% at the mean), increased the unemployment by 1.7% (or 36% at the mean) and increased the probability of having a single job (compared to multiple jobs) by 1.3% (or 1.4% at the mean). The national lockdown decreased full-time employment by 7.5% (or 14% at the mean) and the weekly working hours by 2.5 hours. Moreover, COVID-19 and the national lockdown decreased the probability of working on Fridays by 5%-9%, while the lockdown also decreased the probability of working on Thursdays and Saturdays by 1%-1.4%. An examination of the reported reasons for working fewer hours than usual shows that Australians have been working less than usual since the beginning of COVID-19 and following the lockdown because there is not enough work or because they have left or lost their job. Moreover, individuals significantly prefer to work more hours and are more likely to be actively looking for a job during the pandemic and the lockdown.

Interaction effects show that the adverse effects of COVID-19 on the LFP are smaller for people who have certificate degrees, are married, have childcare-aged kids and have occupations suitable for

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remote work. Importantly, the negative effects of COVID-19 on unemployment are much larger for immigrants and individuals with shorter job tenure. Immigrants and people aged 35-54 are less likely to report self-employment due to the pandemic. The working hours of individuals who are male, are aged 15-34, have shorter job tenure, and have high school education or below declined more than the working hours of others during the pandemic. However, people who have certificate degrees and have jobs suitable for remote work increased their working hours during the pandemic.

The negative effects of the national lockdown on the LFP are lower for people who are married, are aged 55-70, have longer job tenure, have more than a high school education and have childcare-aged kids, and whose occupations are suitable for remote work. On the other hand, workers who are immigrants, cannot work from home and have shorter tenure are more likely to become unemployed during the lockdown. Individuals who are aged 35-54 and have shorter tenure are less likely to report self-employment due to the lockdown. In addition, unmarried men with longer tenure and childcare-aged kids are less likely to have single jobs, compared to having multiple jobs, during the lockdown. The lockdown reduced the working hours of individuals aged 15-34 more than others, while those in occupations suitable for remote work and with longer job tenure and certificate degrees were least affected by the lockdown in terms of working hours.

Our study is related to the emerging literature on COVID-19 that studies the effects of the current pandemic and associated policies on the labour market (Adams-Prassl et al., 2020; Atkeson, 2020; Baek et al., 2020; Baker et al., 2020; Bartik et al., 2020; Beland et al., 2020a; Beland et al., 2020b; Berger et al., 2020; Binder, Forthcoming; Brodeur et al., 2020; Couch et al., 2020; Engle et al., 2020; Fetzer et al., 2020; Hassan et al., 2020; Kahn et al., 2020; Rojas et al., 2020), gender equality (Alon et al., 2020), future careers (Baert et al., 2020), immigrant employment (Borjas and Cassidy, 2020), financial markets (Ramelli and Wagner, 2020), political beliefs (Painter and Qiu, 2020) and election results (Bisbee and Honig, 2020). Our study is also related to a broader body of literature studying the effects of diseases and pandemics (Ma et al., 2020) on health services (Case and Paxson, 2011), school attendance (Goulas and Megalokonomou, 2020) and human capital development (Beach et al., 2018).

The rest of the paper is structured as follows. Section 2 describes the empirical strategy and the variables used in the analysis and presents summary statistics. Section 3 presents the empirical results, while Section 4 concludes.

2. Empirical Strategy and Data

We estimate the short-term effects of COVID-19 and the national lockdown on Australian labour market outcomes. Our empirical approach is based on a simple pre/post analysis at the national level. The baseline specification is estimated using person fixed effects as follows:

$$Y_{i,s,t} = \beta_0 + \beta_1 \, CL_t + \gamma \, X_{i,s,t} + \theta_s + \zeta_t + \alpha_i + \varepsilon_{i,s,t}, \qquad (1)$$

where $Y_{i,s,t}$ is a labour market outcome for individual i, in state s and month t. The main variable of interest, CL_t, is either the COVID-19 or lockdown dummy. $X_{i,s,t}$ includes a set of time-varying control variables, while θ_s, ζ_t, and α_i are state, time and individual fixed effects, respectively. Time fixed effects refer to year and month fixed effects. We also control for state-by-year and state-by-month trends. Individual fixed effects control for person-specific factors such as psychological characteristics, state fixed effects for all time-invariant differences across states, year fixed effects for national trend, and month fixed effects control for potential seasonality in labour market conditions. State-by-year and state-by-month fixed effects control for potential state-specific seasonality and trends. $\varepsilon_{i,s,t}$ represents the error term. The model is estimated using OLS, while standard errors are clustered at the person level and are robust to heteroscedasticity. We also estimate the interaction effects of COVID-19 and the national lockdown with several demographic and work characteristics, to investigate heterogeneities.[4]

2.1 Definition of Variables

Outcome Variables:

We use the following labour market outcomes in our regression models, which are measured in the

[4] Interaction effects with household size would inform about risk-sharing and higher contagion risks, while interaction effects with childcare- and school-aged kids would inform about the role of the free childcare policy and the presence of school-aged kids studying online at home during the lockdown.

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reference week: dummy indicators for being in the labour force, unemployed or self-employed, having a single job, working for more than 35 hours (measure of full-time employment), working on a specific day, and working hours in the main job and all jobs. Moreover, we investigate the reasons why respondents worked fewer hours than usual as dummy variables: on leave, sick or injured, had to shift work, had to leave work for personal reasons, on parental leave, not enough work, and began, left or lost a job. We also examine the job search duration in general as the time since last job (in weeks) for the unemployed individuals, underemployment using a dummy variable measuring a preference to work more during the reference week, and job search effort using a binary indicator for actively/passively looking for a job.

Main Independent Variables:

Reference week dates are provided for everyone in the dataset, which allows us to define our main variables of interest with precision. We define our COVID-19 and national lockdown variables as follows: COVID-19 is equal to 1 if the reference week is between 11 March 2020 and 31 May 2020 and 0 if the reference week is between 1 January 2019 and 10 March 2020. Lockdown is equal to 1 if the reference week is between 21 March 2020 and 31 May 2020 and 0 if the reference week is between 1 January 2019 and 20 March 2020.

Other Independent Variables:

The LLFS includes information on demographic characteristics such as gender, age, marital status and education, and work conditions such as tenure, occupational skill-level and 1-digit/3-digit occupation and industry codes of the respondents. We use information on 3-digit occupation codes to construct a continuous Work from Home Index following Dingel and Neima (2020), where higher values indicate occupations that can be done comfortably from home.

2.2 Descriptive Statistics

Table 1 presents the summary statistics for the baseline regression sample. 4% of the sample experienced the Stage 3 national lockdown, while 7.9% were interviewed after the COVID-19 pandemic declaration. Approximately 39% of the sample can work from home, 48% are men, and the average age is 43. 63% of

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the respondents are married, 68% live in urban areas and 30% are immigrants. 39% have completed up to high school, 29% have received some certificate degree, and 30% have a bachelor's degree or above. The average household size is 2.5, while 14% of households have childcare-aged kids (at least one child aged 0-4) and 20% have school-aged kids (at least one child aged 5-14). The mean LFP rate is 74%, while the average unemployment rate is 4.8%. 16% of the employed individuals are self-employed and 94% have one job, while 54% are working full-time. The average number of working hours in the reference week is 31. Around 76% of the sample worked on Mondays, 82% on Tuesdays, Wednesdays and Thursdays, and 77% on Fridays, while only 24% worked on Saturdays and 16% worked on Sundays. Regarding the reasons why respondents might have worked less than usual in the reference week, 9% reported being on leave or flex-time, 3% reported being ill or injured, 3% had other work arrangements, 1.9% reported personal reasons and 0.7% were on parental leave. 2.8% reported that there was not enough work available, and 0.3% had lost jobs. 14% of the sample would prefer to work more hours, 6% were waiting to start work, and 4% were actively looking for work. The average duration of job search is 54 weeks, and the average duration since last job is 109 weeks.

3. Empirical Results

Table 2 examines the effects of the COVID-19 pandemic and the associated lockdown on labour market outcomes, estimating Equation (1). We present the estimates for COVID-19 and the national lockdown in Panels A and B, respectively. Each column presents a different regression using seven outcome variables (LFP, unemployment, self-employment, single job, a working 35+ hours dummy (full-time employment), and working hours in all jobs and main job). We find that COVID-19 decreased LFP by 2.1% (2.8% at the mean), increased unemployment by 1.1% (24% at the mean), decreased full-time employment by 4.2% (7.8% at the mean), and decreased weekly working hours by 1 hour. In addition, the associated national lockdown led to a 3.2% (4.3% at the mean) decrease in the LFP, a 1.7% (36% at the mean) increase in unemployment, a 1.3% (1.4% at the mean) increase in the probability of having a single job compared to having multiple jobs, a 7.5% (14% at the mean) decrease in the full-time employment, and a 2.5-hour decrease in weekly working hours. Overall, we find that COVID-19 and the national lockdown had significant negative effects on the Australian labour market, in line with previous literature (Beland et al., 2020a; Beland et al., 2020b). In addition, the negative effects of the national lockdown on labour market outcomes in Australia are twice as large as those of COVID-19.

Table 3 investigates the effects of the COVID-19 pandemic and the associated lockdown on workdays (Panel A), underemployment (Panel B) and job searches (Panel C) in Australia. Panel A finds that COVID-19 and the national lockdown decreased the probability of working on Fridays by 5%-9% (7%-12% at the mean), while the national lockdown decreased the probabilities of working on Saturdays and Thursdays by 1% and 1.4% (4% and 1.7% at the mean), respectively. This implies that the reduction in working hours reported in the previous table could be explained partly by not working on certain days. Panel B shows that both COVID-19 and the national lockdown significantly increase the reporting of "not enough work available," and "began, left or lost a job," and significantly decrease the reporting of "personal reasons," and "own illness and injury" as reasons for working less than usual in the reference week. In addition, individuals are more likely to report being on leave or flex-time and having work arrangement or shifts to explain reduced working hours during the national lockdown. The effects of the national lockdown are generally larger. For instance, lockdown increases the probability of reporting "not enough work available" by 8%, while this number is 5% for COVID-19. These results support our initial findings and suggest that the COVID-19 and national lockdown related increase in unemployment can be explained by job losses and not having enough jobs available in the labour market. Panel C finds that COVID-19 and the national lockdown both significantly increase the proportions of people who would prefer to work more, are waiting to start work and are actively looking for work. This result could be explained simply by individuals' own unemployment or the unemployment of other household members, because we find that the national lockdown increased the number of unemployed people in households significantly.

Table 4 examines the interaction effects of COVID-19 on labour market outcomes. Each panel-column presents a different regression. Our results in Panel A suggest that the adverse effects of COVID-19 on the LFP are smaller for people who have jobs suitable for remote work, certificate degrees and

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childcare-aged kids, as well as for those who are aged 35-54 and married. However, Panel B finds that COVID-19 increased the unemployment of immigrants and individuals with shorter job tenure more than others. Indeed, immigrants are twice as likely to become unemployed as the average Australian during the pandemic. The pandemic caused several businesses to shut down due to lower demand and consumption. Our results in Panel C show that immigrants and individuals aged 35-54 were the main victims of the pandemic in terms of reduced self-employment. Panels E, F and G find that COVID-19 reduced the working hours of individuals who are men and aged 15-34, have high school education and below, occupations unsuitable for remote work, shorter job tenure and school-aged kids in the household even further than others. Interestingly, some people whose jobs are suitable for working from home actually experienced an increase in working hours during the pandemic. COVID-19 decreased the weekly working hours of the general population by 2.09 hours but increased the working hours of some people whose jobs are perfectly suitable for remote work (work from home index equals 1) by 0.33 hours. Overall, our findings suggest that COVID-19 did not affect the labor market outcomes of the general population equally, leading to strong inequalities.

Next, **Table 5** investigates the interaction effects of the national lockdown on labour market outcomes. Each panel-column presents a different specification. Panel A finds that the negative effects of the national lockdown on LFP are lower for people who have more than a high school education and longer job tenure, have jobs that can be done at home, have childcare-aged kids, are married and are aged 15-34. Panel B shows that the national lockdown increased the unemployment of immigrants, individuals with shorter job tenures and those who cannot work from home more than others. Indeed, immigrants were twice as likely to become unemployed as the average Australian during the lockdown period.

Panel C reports that individuals who have shorter job tenure and are between 35 and 54 are less likely to be self-employed during the lockdown. Moreover, men and respondents with longer job tenure are more likely to maintain more than one job (Panel D). The interaction effects of lockdown on full-time employment in Panel E show that individuals from immigrant backgrounds, with a bachelor’s degree or above, who cannot work from home and are men experienced lower full-time employment than others due to the lockdown.

Panels F and G report that immigrants, people with high school education and below, those aged 15-34 and those unable to work from home experienced much larger reductions in their working hours due to the national lockdown than others. In summary, we find strong heterogeneities in the adverse effects of the national lockdown on the labor market, suggesting that the pandemic-related lockdown could have increased labour market inequalities in Australia.

3.1 Additional Analysis

Unreported regressions reveal that our estimates are robust to over-controlling and using population weights. Moreover, our findings remained similar when we replaced state of residence with labour market regions and considered January 2018-May 2020, January 2017-May 2020 and January 2016-May 2020 as alternative regression samples. Additional unreported regressions find strong non-linearities when studying the interaction effects with job tenure. The adverse impact of the pandemic and national lockdown on LFP, unemployment and working hours is strongest for people who report job tenures of up to five years. We also find that immigrants who have been living in Australia for up to nine years were hit hardest by the pandemic and lockdown. Moreover, our results document that adults in lone-partnered households experienced a larger reduction in LFP because of the pandemic and the national lockdown. We also find that the adverse effects of COVID-19 and the lockdown on LFP, unemployment and working hours are higher for immigrants who were born in a non-English-speaking country than for people born in Australia.

Furthermore, we examine the differential effects of the pandemic and lockdown by industry and occupation using the following variables: occupational skill, main field of qualification, 1-digit industry and occupation groups. It is highly likely that occupational skills and qualifications are strong predictors of the industry and occupation of workers. Our findings show that the adverse effects of the pandemic and lockdown decline with occupational skills, probably because occupational skills are correlated highly with an occupation's suitability for remote work. Interestingly, people with education qualifications experienced an increase of around 3.5 hours in their weekly working hours due to the pandemic. Individuals with food,

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hospitality and personal services qualifications experienced the largest declines in their weekly working hours (about 5 hours decrease due to the pandemic and 10 hours decrease due to lockdown). On the other hand, interaction effects with the main occupation groups show that community and professional service workers were hit the hardest by the pandemic and associated lockdown in terms of their labour market outcomes: compared to managers and administrators, their LFP reduced by 2%-7%, unemployment increased by around 2%, and working hours declined by 2-3 hours. However, professionals and clerical and administrative workers worked around three hours longer than managers and administrators due to the pandemic and associated lockdown.

In terms of heterogeneities across industries, individuals working in wholesale trade, retail trade, accommodation, transport/postal/warehousing, real-estate, administrative and arts/recreation experienced the largest declines in LFP, with that of people working in arts and recreation declining the most, by 19% compared to those in agriculture/forestry/fishing. Interestingly, the lockdown resulted in some people who worked in wholesale trade, retail trade, accommodation, transport/postal/warehousing becoming self-employed rather than being an employee. The pandemic and the lockdown also left more people working in arts and recreation holding a single job. In line with the LFP results, individuals who worked in wholesale trade, retail trade, accommodation, transport/postal/warehousing, administrative, and arts and recreations experienced the largest decline in their working hours, with the working hours of people working in accommodation, arts and recreations declining the most, by five hours due to the pandemic and 10 hours due to the lockdown. However, individuals working in education and public administration and safety increased their working hours during the pandemic.

Furthermore, we find that individuals are 1.2% more likely to expect to continue working for the current employer as a result of the pandemic/lockdown. As the LLFS asks such expectations only of employed individuals, this implies that people who kept their jobs, during the lockdown, expect to remain employed by their employer probably due to unavailability of jobs elsewhere. Interestingly, 95% people who "expected to work in the next 12 months" before the pandemic/lockdown remained employed however

85% of those who “did not expect to be working in the next 12 months” were observed to be working during the pandemic/lockdown period.

3.2 Our Estimates Compared to Studies in Other Countries

Our findings are in the same direction as the previous literature studying the effects of COVID-19 and lockdown policies on the labour markets in other countries. However, our estimates are smaller in magnitude than those reported in other studies. For example, Beland et al. (2020a) find that in the U.S., COVID-19 increased unemployment by around 10% and decreased LFP by 3.5%. In addition, Beland et al. (2020b) report that COVID-19 led to a 5% increase in unemployment and a 3.7% decrease in LFP in Canada. Therefore, we can argue that the current pandemic/lockdown has not hit the Australian labour market as hard as it has other countries. One potential explanation for this difference is the generosity of the Australian government, which has tried to ease the adverse effects of the pandemic by supporting the labour market. The government implemented a job-keeper program that paid employees’ wages for eligible businesses that experienced a significant decline in their turnover, as well as increasing the welfare payments to unemployed individuals under a job-seeker payment program, and providing free childcare for all Australian residents. It is also important to note that during our regression period, both the number of confirmed cases and the death rate were much lower in Australia than in many other countries across the world. Indeed, it is argued that Australia’s decision to limit and control the movement of people across its borders earlier helped to control the virus’ spread. Australia had around 7,300 confirmed cases with 103 deaths whereas the US had approximately 1.8 million confirmed cases with 102,640 deaths by the end of our regression period (1 June 2020). However, we do not consider using the numbers of COVID-19 cases and deaths as proxies for the regional severity of the pandemic in our regression analysis, due to the low variation in the case numbers and death rates across states and cities in Australia during the regression period, unlike the previous literature in the US (Beland et al., 2020a).

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5. Conclusion

We study the short-term labour market effects of COVID-19 and the associated national lockdown in Australia by estimating person fixed effects models using longitudinal data. COVID-19 decreased LFP by 2.1% (2.8% at the mean), increased unemployment by 1.1% (24% at the mean), decreased full-time employment by 4% (7.8% at the mean), and decreased weekly working hours by 1.1. On the other hand, the national lockdown decreased LFP by 3.2% (4.3% at the mean), increased unemployment by 1.7% (36% at the mean), decreased full-time employment by 7.5% (14% at the mean), and decreased weekly working hours by 2.5 hours, but increased the probability of having only one job by 1.3% (1.4% at the mean). The probability of working on Fridays decreased by 10%, but working fewer hours due to being on leave, working shifts, not having enough work and losing jobs increased due to the lockdown. The pandemic and the lockdown also increased underemployment and job search efforts significantly.

In particular, the negative effects of the national lockdown on the LFP were smaller for people with longer job tenures, more than a high school education, childcare-aged kids, and occupations suitable for remote work. This implies that the free childcare policy may have successfully increased the LFP of parents with childcare-aged kids during the lockdown. On the other hand, workers who are immigrants, cannot work from home and have shorter tenures are more likely to become unemployed due to the lockdown. Individuals aged 35-54 with shorter tenures were less likely to report self-employment due to the lockdown. The lockdown reduced the working hours of individuals aged 15-34 more than others, while those with occupations suitable for remote work, longer job tenures and certificate degrees were affected least by the lockdown in terms of working hours.

The adverse impact of the pandemic and national lockdown on LFP, unemployment and working hours is worse for people with less than five years of job tenure and for immigrants from non-English-speaking countries who have been living in Australia for less than nine years. Moreover, adults in lone-parent families experienced larger reductions in their LFP due to the national lockdown. Interaction effects reveal that people with education qualifications worked around 3.5 hours longer due to the pandemic.

However, the largest declines in weekly working hours (about 5 hours decrease due to the pandemic and 10 hours decrease due to lockdown) were experienced by those with food, hospitality and personal services qualifications. Interaction effects with occupations reveal that community and professional service workers were hit the hardest by the pandemic and the lockdown in terms of their labour market outcomes: their LFP reduced by 4%-10%, unemployment increased by around 2%, and working hours declined by 2-5 hours. However, professionals and clerical and administrative workers worked longer hours due to the pandemic and the lockdown. In terms of heterogeneities across industries, LFP and working hours declined the most for people working in arts and recreations due to pandemic/lockdown but individuals working in education and public administration and safety increased their working hours during the pandemic.

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Table 1: Summary Statistics

	Mean	Standard Deviation	Minimum	Maximum	Non-missing Observations
Independent Variables:					
Lockdown	0.040	0.196	0.000	1.000	279368
Covid-19	0.079	0.270	0.000	1.000	279368
Work From Home Index	0.389	0.393	0.000	1.000	214080
Male	0.487	0.500	0.000	1.000	279368
Age	43.445	15.437	15.000	70.000	279368
Married	0.629	0.483	0.000	1.000	279368
Bachelor Degree and Above	0.295	0.456	0.000	1.000	279368
Certificate Degree	0.285	0.451	0.000	1.000	279368
High School Degree and Below	0.390	0.488	0.000	1.000	279368
Urban Residence	0.684	0.465	0.000	1.000	279368
Immigrant	0.301	0.459	0.000	1.000	279309
Number of People in the Household	2.516	1.105	1.000	10.000	279368
Childcare Aged Kids	0.145	0.352	0.000	1.000	279368
School Aged Kids	0.203	0.402	0.000	1.000	279368
Dependent Variables:					
In the Labour Force	0.744	0.437	0.000	1.000	279368
Unemployed	0.048	0.214	0.000	1.000	207803
Selfemployed (vs Employee)	0.162	0.369	0.000	1.000	197443
Single Job (vs Multiple Jobs)	0.942	0.234	0.000	1.000	197784
Working 35+ Hours Dummy	0.543	0.498	0.000	1.000	197784
Working Hours (All Jobs)	31.673	17.210	0.000	99.000	197784
Working Hours (Main Job)	31.091	17.035	0.000	99.000	197784
Whether Worked on a Specific Day In the Reference Week:					
Work on Monday	0.762	0.426	0.000	1.000	182478
Work on Tuesday	0.819	0.385	0.000	1.000	182478
Work on Wednesday	0.822	0.383	0.000	1.000	182478
Work on Thursday	0.818	0.386	0.000	1.000	182478
Work on Friday	0.771	0.420	0.000	1.000	182478
Work on Saturday	0.236	0.425	0.000	1.000	182478
Work on Sunday	0.164	0.370	0.000	1.000	182478
Reasons Why Worked Less than Usual in the Reference Week:					
On Leave or Flextime	0.091	0.288	0.000	1.000	247483
Own Illness or Injury	0.031	0.173	0.000	1.000	232081
Work Arrangements or Shift Work	0.030	0.172	0.000	1.000	231965
Personal Reasons	0.019	0.137	0.000	1.000	229341
Parental Leave	0.007	0.084	0.000	1.000	226529
Not Enough Work Available	0.028	0.165	0.000	1.000	231369
Began, Left or Lost a Job	0.003	0.054	0.000	1.000	225590
Job Search and Unemployment:					
Prefer to Work More	0.141	0.348	0.000	1.000	279368
Duration of Job Search (Unemployed)	54.552	98.498	1.000	NA	10019
Duration since Last Job (Unemployed)	109.464	188.782	1.000	NA	8171
Waiting to Start Work	0.006	0.077	0.000	1.000	209042
Actively Looking for Work	0.004	0.064	0.000	1.000	208671
Passively Looking for Work	0.007	0.083	0.000	1.000	209255
Number of Unemployed People in Household	0.098	0.332	0.000	4.000	279368

Notes: The summary statistics are presented for the regression sample that consists of individuals whose reference week is between 1 January 2019 and 31 March 2020 and are aged 15-70. COVID-19 is equal to 1 if the reference week is between 11 March 2020 and 31 May 2020 and 0 if reference week is between 1 January 2019 and 10 March 2020. Lockdown is equal to 1 if the reference week is between 21 March 2020 and 31 May 2020 and 0 if reference week is between 1 January 2019 and 20 March 2020. High School Degree and Below: Completed up to year 12 or less. Certificate Degree: Received some certificate degree or diploma. Bachelor Degree and Above: Received some bachelor degree and/or completed postgraduate studies. Childcare Aged Kids is a dummy variable and is equal to 1 if there is at least one child aged zero to four in the household and 0 otherwise. School Aged Kids is a dummy variable and is equal to 1 if there is at least one child aged five to fourteen in the household and 0 otherwise. Work From Home Index is a continuous variable and higher values are assigned to occupations that can be done from home.

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Table 2: Effects of Covid-19 and National Lockdown on Labour Market Outcomes in Australia

Outcome Variable→	(1) In the Labour Force	(2) Unemployed	(3) Selfemployed (vs Employee)	(4) Single Job (vs Multiple Jobs)	(5) Working 35+ Hours Dummy	(6) Working Hours (All Jobs)	(7) Working Hours (Main Job)
Panel A: Effects of Covid-19							
Covid-19	-0.0211***	0.0118***	0.00155	0.00497*	-0.0426***	-1.108***	-1.095***
	(6.78)	(4.56)	(0.72)	(1.65)	(6.41)	(4.77)	(4.77)
Age	0.0164***	-0.0207***	0.00108	0.00262	0.0135	0.836***	0.804***
	(3.33)	(5.03)	(0.38)	(0.56)	(1.61)	(2.87)	(2.81)
Age-squared	-0.0201***	0.0262***	-0.00234	-0.00200	-0.0255***	-1.249***	-1.223***
	(3.99)	(6.01)	(0.73)	(0.40)	(2.77)	(3.82)	(3.80)
Bachelor Degree and Above	0.0469***	-0.000237	-0.000754	-0.00534	-0.00444	0.211	0.131
	(4.48)	(0.03)	(0.19)	(0.69)	(0.30)	(0.43)	(0.27)
Certificate Degree	0.0682***	0.00199	0.00606	-0.00563	0.0358*	1.072	1.096*
	(4.58)	(0.19)	(1.10)	(0.40)	(1.74)	(1.61)	(1.68)
Married	0.00336	-0.0144	-0.00946	-0.000333	-0.00808	0.525	0.358
	(0.26)	(1.44)	(1.00)	(0.03)	(0.37)	(0.67)	(0.47)
Number of Observations	279368	207803	197443	197784	197784	197784	197784
Panel B: Effects of National Lockdown							
Lockdown	-0.0326***	0.0176***	0.00191	0.0134***	-0.0757***	-2.502***	-2.385***
	(10.16)	(6.67)	(0.92)	(4.57)	(11.24)	(10.76)	(10.44)
Age	0.0164***	-0.0207***	0.00108	0.00265	0.0134	0.832***	0.800***
	(3.33)	(5.02)	(0.38)	(0.56)	(1.59)	(2.86)	(2.80)
Age-squared	-0.0201***	0.0261***	-0.00234	-0.00207	-0.0252***	-1.236***	-1.212***
	(3.98)	(6.00)	(0.73)	(0.41)	(2.73)	(3.78)	(3.77)
Bachelor Degree and Above	0.0468***	-0.000270	-0.000762	-0.00530	-0.00440	0.207	0.128
	(4.48)	(0.03)	(0.19)	(0.69)	(0.29)	(0.42)	(0.26)
Certificate Degree	0.0683***	0.00199	0.00606	-0.00566	0.0359*	1.076	1.099*
	(4.59)	(0.19)	(1.11)	(0.41)	(1.74)	(1.61)	(1.69)
Married	0.00335	-0.0144	-0.00945	-0.000325	-0.00820	0.523	0.355
	(0.26)	(1.43)	(1.00)	(0.03)	(0.37)	(0.67)	(0.46)
Number of Observations	279368	207803	197443	197784	197784	197784	197784
Person FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State*Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State*Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: OLS regressions. Each panel-column displays estimates from a different regression. COVID-19 is equal to 1 if the reference week is between 11 March 2020 and 31 May 2020 and 0 if reference week is between 1 January 2019 and 10 March 2020. Lockdown is equal to 1 if the reference week is between 21 March 2020 and 31 May 2020 and 0 if reference week is between 1 January 2019 and 20 March 2020. Age-squared has been divided by 100. The reference categories are High School Degree and Below and Not Married. Robust standard errors are clustered at the person-level. Absolute t-statistics are presented in parantheses. * , ** and *** indicate significance at the 10%, 5% and 1% level respectively.

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Table 3: Effects of Covid-19 and National Lockdown on Work Days, Underemployment and Job Search in Australia

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Panel A: Outcome Variable: Whether Worked on a Specific Day In the Reference Week														
Outcome Variable→	**Work on Monday**		**Work on Tuesday**		**Work on Wednesday**		**Work on Thursday**		**Work on Friday**		**Work on Saturday**		**Work on Sunday**	
Covid-19	0.00156		0.000674		-0.0104*		-0.00682		-0.0541***		-0.00694		-0.00604	
	(0.25)		(0.12)		(1.88)		(1.23)		(8.71)		(1.16)		(1.17)	
Lockdown		-0.00721		-0.00435		-0.00910		-0.0146**		-0.0921***		-0.0101*		-0.00101
		(1.12)		(0.79)		(1.64)		(2.55)		(13.46)		(1.68)		(0.19)
Number of Observations	182478	182478	182478	182478	182478	182478	182478	182478	182478	182478	182478	182478	182478	182478
Panel B: Outcome Variable: Reasons Why Worked Less than Usual in the Reference Week														
Outcome Variable →	**On Leave or Flextime**		**Own Illness or Injury**		**Work Arrangements or Shift Work**		**Personal Reasons**		**Parental Leave**		**Not Enough Work Available**		**Began, Left or Lost a Job**	
Covid-19	-0.00204		-0.00440*		-0.00158		-0.00371*		0.000209		0.0477***		0.0112***	
	(0.46)		(1.73)		(0.58)		(1.71)		(0.18)		(16.37)		(9.52)	
Lockdown		0.0181***		-0.00737***		0.00497*		-0.00492**		-0.000576		0.0761***		0.0188***
		(4.19)		(2.88)		(1.87)		(2.28)		(0.47)		(19.84)		(10.79)
Number of Observations	247483	247483	232081	232081	231965	231965	229341	229341	226529	226529	231369	231369	225590	225590
Panel C: Outcome Variable: Job Search and Unemployment														
Outcome Variable →	**Prefer to Work More**		**Duration of Job Search (Unemployed)**		**Duration since Last Job (Unemployed)**		**Waiting to Start Work**		**Actively Looking for Work**		**Passively Looking for Work**		**Number of Unemployed People in Household**	
Covid-19	0.0109***		1.824		5.062		0.00684***		0.00178*		0.00130		0.00822	
	(2.72)		(0.32)		(0.67)		(4.45)		(1.75)		(1.01)		(1.10)	
Lockdown		0.00837**		-2.096		-5.306		0.00926***		0.00176*		0.00199		0.0171**
		(2.10)		(0.35)		(0.66)		(6.01)		(1.82)		(1.62)		(2.26)
Number of Observations	279368	279368	10019	10019	8171	8171	209042	209042	208671	208671	209255	209255	279368	279368
Person FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State*Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State*Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: OLS regressions. Each panel-column displays estimates from a different regression. COVID-19 is equal to 1 if the reference week is between 11 March 2020 and 31 May 2020 and 0 if reference week is between 1 January 2019 and 10 March 2020. Lockdown is equal to 1 if the reference week is between 21 March 2020 and 31 May 2020 and 0 if reference week is between 1 January 2019 and 20 March 2020. Robust standard errors are clustered at the person-level. Robust standard error are clustered at the household-level in Panel C, Columns 13 and 14. Absolute t-statistics are presented in parantheses. * , ** and *** indicate significance at the 10%, 5% and 1% level respectively.

Table 4: Interaction Effects of COVID-19

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: Outcome Variable: In the Labour Force										
Covid-19	-0.0324*** (7.47)	-0.0184*** (5.06)	-0.0250*** (6.38)	-0.0294*** (7.00)	-0.0232*** (6.20)	-0.0195*** (4.99)	-0.0207*** (6.32)	-0.0206*** (5.34)	-0.0174*** (3.35)	-0.0254*** (7.73)
Covid-19*Work From Home Index	0.0239*** (4.70)									
Covid-19*Male		-0.00550 (1.56)								
Covid-19*Bachelor Degree and Above			0.00232 (0.54)							
Covid-19*Certificate Degree			0.0109*** (2.58)							
Covid-19*Married				0.0132*** (3.40)						
Covid-19*Aged 15-34					-0.00167 (0.35)					
Covid-19*Aged 35-54					0.00638* (1.73)					
Covid-19*Tenure						0.000254 (0.99)				
Covid-19*Immigrant							-0.00141 (0.35)			
Covid-19*Urban Residence								-0.000719 (0.20)		
Covid-19*Number of People in Household									-0.00147 (0.84)	
Covid-19*Childcare Aged Kids										0.0233*** (3.92)
Covid-19*School Aged Kids										0.00593 (1.27)
Panel B: Outcome Variable: Unemployed										
Covid-19	0.0139*** (4.49)	0.0111*** (3.76)	0.0120*** (3.41)	0.00999*** (2.73)	0.0146*** (4.25)	0.0151*** (5.02)	0.00888*** (3.30)	0.00882*** (2.70)	0.0134*** (3.07)	0.0127*** (4.43)
Covid-19*Work From Home Index	-0.00173 (0.48)									
Covid-19*Male		0.00126 (0.42)								
Covid-19*Bachelor Degree and Above			0.000208 (0.05)							
Covid-19*Certificate Degree			-0.000853 (0.23)							
Covid-19*Married				0.00275 (0.80)						
Covid-19*Aged 15-34					-0.00499 (1.19)					
Covid-19*Aged 35-54					-0.00241 (0.72)					
Covid-19*Tenure						-0.000369** (2.03)				
Covid-19*Immigrant							0.0103*** (2.88)			
Covid-19*Urban Residence								0.00436 (1.41)		
Covid-19*Number of People in Household									-0.000620 (0.42)	
Covid-19*Childcare Aged Kids										-0.00528 (1.29)
Covid-19*School Aged Kids										-0.000611 (0.17)
Panel C: Outcome Variable: Self-employed (versus Employee)										
Covid-19	0.00256 (1.02)	0.00268 (1.11)	0.00115 (0.45)	0.00203 (0.76)	0.00664** (2.24)	0.00131 (0.50)	0.00319 (1.43)	0.000197 (0.07)	0.00244 (0.69)	0.00304 (1.32)
Covid-19*Work From Home Index	-0.00278 (0.88)									
Covid-19*Male		-0.00218 (0.90)								
Covid-19*Bachelor Degree and Above			0.00193 (0.65)							
Covid-19*Certificate Degree			-0.000583 (0.21)							
Covid-19*Married				-0.000698 (0.28)						
Covid-19*Aged 15-34					-0.00346 (1.06)					
Covid-19*Aged 35-54					-0.00864*** (2.97)					
Covid-19*Tenure						-0.0000229 (0.12)				
Covid-19*Immigrant							-0.00543* (1.82)			
Covid-19*Urban Residence								0.00199 (0.76)		
Covid-19*Number of People in Household									-0.000344 (0.30)	
Covid-19*Childcare Aged Kids										-0.00562 (1.28)
Covid-19*School Aged Kids										-0.00307 (1.10)
Panel D: Outcome Variable: Single Job (versus Multiple Jobs)										
Covid-19	0.00484 (1.40)	0.00456 (1.26)	0.00473 (1.29)	0.00364 (0.91)	0.00437 (1.07)	0.00686* (1.90)	0.00487 (1.52)	0.00459 (1.14)	-0.00457 (0.93)	0.00511 (1.57)
Covid-19*Work From Home Index	0.000389 (0.09)									
Covid-19*Male		0.000789 (0.24)								
Covid-19*Bachelor Degree and Above			0.00469 (1.21)							
Covid-19*Certificate Degree			-0.00351 (0.89)							
Covid-19*Married				0.00198 (0.54)						
Covid-19*Aged 15-34					0.00178 (0.39)					
Covid-19*Aged 35-54					0.000180 (0.05)					
Covid-19*Tenure						-0.000359 (1.54)				
Covid-19*Immigrant							0.000357 (0.10)			
Covid-19*Urban Residence								0.000557 (0.15)		
Covid-19*Number of People in Household									0.00376** (2.51)	
Covid-19*Childcare Aged Kids										-0.00336 (0.70)
Covid-19*School Aged Kids										0.00151 (0.39)
Panel E: Outcome Variable: Working 35+ Hours Dummy										
Covid-19	-0.0588*** (7.62)	-0.0301*** (3.99)	-0.0556*** (6.73)	-0.0426*** (5.01)	-0.0354*** (3.75)	-0.0477*** (6.10)	-0.0389*** (5.54)	-0.0361*** (4.13)	-0.0521*** (4.65)	-0.0464*** (6.36)
Covid-19*Work From Home Index	0.0401*** (4.11)									
Covid-19*Male		-0.0242*** (3.21)								
Covid-19*Bachelor Degree and Above			-0.00592 (0.63)							
Covid-19*Certificate Degree			0.0423*** (4.78)							
Covid-19*Married				-0.0000584 (0.01)						
Covid-19*Aged 15-34					-0.0167 (1.62)					
Covid-19*Aged 35-54					-0.00508 (0.53)					
Covid-19*Tenure						0.00115** (2.00)				
Covid-19*Immigrant							-0.0134 (1.57)			
Covid-19*Urban Residence								-0.00957 (1.16)		
Covid-19*Number of People in Household									0.00372 (1.06)	
Covid-19*Childcare Aged Kids										-0.00414 (0.38)
Covid-19*School Aged Kids										0.0193** (2.12)
Panel F: Outcome Variable: Working Hours (All Jobs)										
Covid-19	-2.085*** (7.68)	-0.845*** (3.26)	-2.033*** (7.09)	-1.378*** (4.88)	-1.027*** (3.13)	-1.406*** (5.22)	-1.020*** (4.16)	-0.740** (2.37)	-1.231*** (3.25)	-1.376*** (5.48)
Covid-19*Work From Home Index	2.417*** (7.14)									
Covid-19*Male		-0.512** (1.99)								
Covid-19*Bachelor Degree and Above			0.158 (0.49)							
Covid-19*Certificate Degree			2.487*** (8.31)							
Covid-19*Married				0.399 (1.51)						
Covid-19*Aged 15-34					-0.804** (2.30)					
Covid-19*Aged 35-54					0.328 (1.00)					
Covid-19*Tenure						0.0617 (3.09)***				
Covid-19*Immigrant							-0.308 (1.06)			
Covid-19*Urban Residence								-0.541* (1.85)		
Covid-19*Number of People in Household									0.0477 (0.41)	
Covid-19*Childcare Aged Kids										-0.145 (0.36)
Covid-19*School Aged Kids										1.278*** (4.07)
Panel G: Outcome Variable: Working Hours (Main Job)										
Covid-19	-2.080*** (7.78)	-0.828*** (3.25)	-2.076*** (7.33)	-1.346*** (4.83)	-1.061*** (3.26)	-1.375*** (5.19)	-0.994*** (4.11)	-0.754** (2.45)	-1.228*** (3.28)	-1.359*** (5.48)
Covid-19*Work From Home Index	2.440*** (7.34)									
Covid-19*Male		-0.517** (2.04)								
Covid-19*Bachelor Degree and Above			0.304 (0.95)							
Covid-19*Certificate Degree			2.520*** (8.58)							
Covid-19*Married				0.373 (1.44)						
Covid-19*Aged 15-34					-0.730** (2.12)					
Covid-19*Aged 35-54					0.382 (1.17)					
Covid-19*Tenure						0.0579*** (2.93)				
Covid-19*Immigrant							-0.350 (1.22)			
Covid-19*Urban Residence								-0.500* (1.74)		
Covid-19*Number of People in Household									0.0520 (0.45)	
Covid-19*Childcare Aged Kids										-0.175 (0.45)
Covid-19*School Aged Kids										1.284*** (4.16)

Notes: OLS regressions. Each panel-column displays estimates from a different regression. All regressions include demographic controls, person fe, state fe, year fe, month fe, state by year fe, state by month as well as the main effect of the interaction variable. COVID-19 is equal to 1 if the reference week is between 11 March 2020 and 31 May 2020 and 0 if reference week is between 1 January 2019 and 10 March 2020. Certificate Degree: Received some certificate degree or diploma. Bachelor Degree and Above: Received some bachelor degree and/or completed postgraduate studies. School Aged Kids is a dummy variable and is equal to 1 if there is at least one child aged zero to four in the household and 0 otherwise. Childcare Aged Kids is a dummy variable and is equal to 1 if there is at least one child aged five to fourteen in the household and 0 otherwise. Work From Home Index is a continuous variable and higher values are assigned to occupations that can be done from home. Robust standard errors are clustered at the person-level. Absolute t-statistics are presented in parantheses. * , ** and *** indicate significance at the 10%, 5% and 1% level respectively.

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Table 5: Interaction Effects of National Lockdown

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: Outcome Variable: In the Labour Force										
Lockdown	-0.0561*** (10.84)	-0.0302*** (7.30)	-0.0469*** (9.86)	-0.0545*** (10.46)	-0.0277*** (6.41)	-0.0417*** (8.71)	-0.0309*** (8.87)	-0.0270*** (5.92)	-0.0187*** (2.84)	-0.0368*** (10.18)
Lockdown*Work From Home Index	0.0471*** (6.55)									
Lockdown*Male		-0.00499 (1.01)								
Lockdown*Bachelor Degree and Above			0.0176*** (2.88)							
Lockdown*Certificate Degree			0.0303*** (5.13)							
Lockdown*Married				0.0345*** (6.24)						
Lockdown*Aged 15-34					-0.0255*** (3.73)					
Lockdown*Aged 35-54					0.00669 (1.29)					
Lockdown*Tenure						0.00143*** (3.72)				
Lockdown*Immigrant							-0.00606 (1.04)			
Lockdown*Urban Residence								-0.00838 (1.62)		
Lockdown*Number of People in Household									-0.00550** (2.25)	
Lockdown*Childcare Aged Kids										0.0218*** (2.85)
Lockdown*School Aged Kids										0.00628 (0.94)
Panel B: Outcome Variable: Unemployed										
Lockdown	0.0245*** (6.46)	0.0171*** (5.05)	0.0184*** (4.26)	0.0185*** (3.99)	0.0142*** (3.73)	0.0256*** (6.88)	0.0125*** (4.45)	0.0137*** (3.56)	0.0146*** (2.64)	0.0180*** (5.69)
Lockdown*Work From Home Index	-0.0163*** (3.10)									
Lockdown*Male		0.000860 (0.20)								
Lockdown*Bachelor Degree and Above			0.00335 (0.61)							
Lockdown*Certificate Degree			-0.00541 (1.04)							
Lockdown*Married				-0.00137 (0.28)						
Lockdown*Aged 15-34					0.00674 (1.13)					
Lockdown*Aged 35-54					0.00294 (0.66)					
Lockdown*Tenure						-0.00106*** (3.99)				
Lockdown*Immigrant							0.0180*** (3.47)			
Lockdown*Urban Residence								0.00568 (1.29)		
Lockdown*Number of People in Household									0.00114 (0.55)	
Lockdown*Childcare Aged Kids										-0.000482 (0.08)
Lockdown*School Aged Kids										-0.00161 (0.32)
Panel C: Outcome Variable: Self-employed (versus Employee)										
Lockdown	0.00425* (1.68)	0.00339 (1.35)	0.00110 (0.41)	0.00286 (1.04)	0.00753** (2.40)	-0.00192 (0.66)	0.00315 (1.43)	0.00226 (0.73)	0.00170 (0.42)	0.00302 (1.35)
Lockdown*Work From Home Index	-0.00550 (1.39)									
Lockdown*Male		-0.00289 (0.95)								
Lockdown*Bachelor Degree and Above			0.00573 (1.51)							
Lockdown*Certificate Degree			-0.00280 (0.83)							
Lockdown*Married				-0.00141 (0.46)						
Lockdown*Aged 15-34					-0.00457 (1.14)					
Lockdown*Aged 35-54					-0.00906** (2.53)					
Lockdown*Tenure						0.000462* (1.95)				
Lockdown*Immigrant							-0.00425 (1.17)			
Lockdown*Urban Residence								-0.000518 (0.16)		
Lockdown*Number of People in Household									0.0000905 (0.07)	
Lockdown*Childcare Aged Kids										-0.00392 (0.72)
Lockdown*School Aged Kids										-0.00250 (0.66)
Panel D: Outcome Variable: Single Job (versus Multiple Jobs)										
Lockdown	0.0167*** (4.29)	0.0183*** (4.53)	0.0127*** (3.18)	0.0196*** (4.24)	0.0127*** (2.71)	0.0175*** (4.18)	0.0131*** (4.01)	0.0137*** (2.94)	0.00639 (1.06)	0.0143*** (4.34)
Lockdown*Work From Home Index	-0.00818 (1.48)									
Lockdown*Male		-0.00937** (2.12)								
Lockdown*Bachelor Degree and Above			0.00363 (0.67)							
Lockdown*Certificate Degree			-0.00103 (0.20)							
Lockdown*Married				-0.00910* (1.85)						
Lockdown*Aged 15-34					0.00567 (0.95)					
Lockdown*Aged 35-54					-0.00190 (0.36)					
Lockdown*Tenure						-0.000678** (2.05)				
Lockdown*Immigrant							0.00120 (0.25)			
Lockdown*Urban Residence								-0.000388 (0.08)		
Lockdown*Number of People in Household									0.00277 (1.41)	
Lockdown*Childcare Aged Kids										-0.0120* (1.77)
Lockdown*School Aged Kids										0.00367 (0.67)
Panel E: Outcome Variable: Working 35+ Hours Dummy										
Lockdown	-0.0991*** (11.36)	-0.0625*** (7.50)	-0.0861*** (8.87)	-0.0731*** (7.38)	-0.0605*** (5.26)	-0.0804*** (9.05)	-0.0685*** (9.25)	-0.0802*** (8.00)	-0.0716*** (5.12)	-0.0779*** (9.91)
Lockdown*Work From Home Index	0.0576*** (4.27)									
Lockdown*Male		-0.0257** (2.45)								
Lockdown*Bachelor Degree and Above			-0.0281** (2.12)							
Lockdown*Certificate Degree			0.0542*** (4.46)							
Lockdown*Married				-0.00380 (0.34)						
Lockdown*Aged 15-34					-0.0258* (1.80)					
Lockdown*Aged 35-54					-0.0164 (1.24)					
Lockdown*Tenure						0.00126 (1.56)				
Lockdown*Immigrant							-0.0265** (2.21)			
Lockdown*Urban Residence								0.00673 (0.60)		
Lockdown*Number of People in Household									-0.00161 (0.34)	
Lockdown*Childcare Aged Kids										0.000842 (0.06)
Lockdown*School Aged Kids										0.00932 (0.73)
Panel F: Outcome Variable: Working Hours (All Jobs)										
Lockdown	-3.886*** (12.53)	-2.592*** (9.04)	-3.272*** (9.52)	-2.643*** (8.01)	-2.309*** (5.59)	-2.895*** (9.35)	-2.306*** (8.97)	-2.279*** (6.32)	-2.278*** (4.69)	-2.682*** (9.93)
Lockdown*Work From Home Index	3.413*** (7.08)									
Lockdown*Male		0.176 (0.48)								
Lockdown*Bachelor Degree and Above			-0.492 (1.04)							
			2.607*** (6.12)							
Lockdown*Married				0.208 (0.55)						
Lockdown*Aged 15-34					-1.074** (2.11)					
Lockdown*Aged 35-54					0.249 (0.53)					
Lockdown*Tenure						0.0791*** (2.72)				
Lockdown*Immigrant							-0.716* (1.70)			
Lockdown*Urban Residence								-0.329 (0.82)		
Lockdown*Number of People in Household									-0.0887 (0.55)	
Lockdown*Childcare Aged Kids										0.0976 (0.17)
Lockdown*School Aged Kids										0.736 (1.63)
Panel G: Outcome Variable: Working Hours (Main Job)										
Lockdown	-3.731*** (12.35)	-2.437*** (8.70)	-3.252*** (9.60)	-2.463*** (7.61)	-2.193*** (5.37)	-2.758*** (9.11)	-2.203*** (8.74)	-2.202*** (6.25)	-2.100*** (4.41)	-2.548*** (9.57)
Lockdown*Work From Home Index	3.318*** (7.02)									
Lockdown*Male		0.101 (0.28)								
Lockdown*Bachelor Degree and Above			-0.291 (0.63)							
Lockdown*Certificate Degree			2.698*** (6.46)							
Lockdown*Married				0.114 (0.31)						
Lockdown*Aged 15-34					-1.059** (2.12)					
Lockdown*Aged 35-54					0.242 (0.52)					
Lockdown*Tenure						0.0735** (2.57)				
Lockdown*Immigrant							-0.665 (1.61)			
Lockdown*Urban Residence								-0.271 (0.69)		
Lockdown*Number of People in Household									-0.112 (0.70)	
Lockdown*Childcare Aged Kids										0.0344 (0.06)
Lockdown*School Aged Kids										0.697 (1.57)

Notes: OLS regressions. Each panel-column displays estimates from a different regression. All regressions include demographic controls, person fe, state fe, year fe, month fe, state by year fe, state by month fe as well as the main effect of the interaction variable. Lockdown is equal to 1 if the reference week is between 21 March 2020 and 31 May 2020 and 0 if reference week is between 1 January 2019 and 20 March 2020. Certificate Degree: Received some certificate degree or diploma. Bachelor Degree and Above: Received some bachelor degree and/or completed postgraduate studies. Childcare Aged Kids is a dummy variable and is equal to 1 if there is at least one child aged zero to four in the household and 0 otherwise. School Aged Kids is a dummy variable and is equal to 1 if there is at least one child aged five to fourteen in the household and 0 otherwise. Work From Home Index is a continuous variable and higher values are assigned to occupations that can be done from home. Robust standard errors are clustered at the person-level. Absolute t-statistics are presented in parantheses. * , ** and *** indicate significance at the 10%, 5% and 1% level respectively.

Appendix Table 1: COVID-19 and Labour Market Effects: Including Control Variables One-by-One in the Regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(9)
	Outcome Variable: In the Labour Force						
Covid-19	-0.0101***	-0.0101***	-0.00907***	-0.0211***	-0.0211***	-0.0212***	-0.0211***
	(5.73)	(5.73)	(5.00)	(6.79)	(6.80)	(6.85)	(6.78)
Number of Observations	279368	279368	279368	279368	279368	279368	279368
	Outcome Variable: Unemployed						
Covid-19	0.00376**	0.00376**	0.00445***	0.0119***	0.0119***	0.0120***	0.0118***
	(2.52)	(2.52)	(2.92)	(4.60)	(4.61)	(4.62)	(4.56)
Number of Observations	207803	207803	207803	207803	207803	207803	207803
	Outcome Variable: Selfemployed (vs Employee)						
Covid-19	-0.00308**	-0.00308**	-0.00218*	0.00161	0.00159	0.00156	0.00155
	(2.54)	(2.54)	(1.81)	(0.74)	(0.73)	(0.72)	(0.72)
Number of Observations	197443	197443	197443	197443	197443	197443	197443
	Outcome Variable: Single Job (vs Multiple Jobs)						
Covid-19	0.0128***	0.0128***	0.00523***	0.00517*	0.00515*	0.00502*	0.00497*
	(7.91)	(7.91)	(3.21)	(1.71)	(1.71)	(1.66)	(1.65)
Number of Observations	197784	197784	197784	197784	197784	197784	197784
	Outcome Variable: Working 35+ Hours Dummy						
Covid-19	-0.0374***	-0.0374***	-0.0147***	-0.0429***	-0.0429***	-0.0427***	-0.0426***
	(9.90)	(9.90)	(3.55)	(6.46)	(6.46)	(6.44)	(6.41)
Number of Observations	197784	197784	197784	197784	197784	197784	197784
	Outcome Variable: Working Hours (All Jobs)						
Covid-19	-0.684***	-0.684***	1.119***	-1.116***	-1.116***	-1.114***	-1.108***
	(5.29)	(5.29)	(7.70)	(4.81)	(4.81)	(4.80)	(4.77)
Number of Observations	197784	197784	197784	197784	197784	197784	197784
	Outcome Variable: Working Hours (Main Job)						
Covid-19	-0.535***	-0.535***	1.161***	-1.100***	-1.101***	-1.099***	-1.095***
	(4.22)	(4.22)	(8.11)	(4.80)	(4.80)	(4.79)	(4.77)
Number of Observations	197784	197784	197784	197784	197784	197784	197784
Person FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	No	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	Yes	Yes	Yes	Yes	Yes
Month FE	No	No	No	Yes	Yes	Yes	Yes
State*Year Inter	No	No	No	No	Yes	Yes	Yes
State*Month Inter	No	No	No	No	No	Yes	Yes
Demographic Controls	No	No	No	No	No	No	Yes

Notes: OLS regressions. Each panel-column displays estimates from a different regression. COVID-19 is equal to 1 if the reference week is between 11 March 2020 and 31 May 2020 and 0 if reference week is between 1 January 2019 and 10 March 2020. Robust standard errors are clustered at the person-level. Absolute t-statistics are presented in parantheses. * , ** and *** indicate significance at the 10%, 5% and 1% level respectively.

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Appendix Table 2: Labour Market Effects of National Lockdown: Including Control Variables One-by-One in the Regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(9)
	Outcome Variable: In the Labour Force						
Lockdown	-0.0255***	-0.0255***	-0.0251***	-0.0326***	-0.0326***	-0.0327***	-0.0326***
	(10.25)	(10.25)	(10.02)	(10.16)	(10.17)	(10.21)	(10.16)
Number of Observations	279368	279368	279368	279368	279368	279368	279368
	Outcome Variable: Unemployed						
Lockdown	0.0120***	0.0120***	0.0128***	0.0177***	0.0177***	0.0177***	0.0176***
	(5.63)	(5.63)	(6.03)	(6.71)	(6.72)	(6.72)	(6.67)
Number of Observations	207803	207803	207803	207803	207803	207803	207803
	Outcome Variable: Selfemployed (vs Employee)						
Lockdown	-0.00149	-0.00149	-0.000409	0.00193	0.00193	0.00190	0.00191
	(0.99)	(0.99)	(0.27)	(0.93)	(0.93)	(0.91)	(0.92)
Number of Observations	197443	197443	197443	197443	197443	197443	197443
	Outcome Variable: Single Job (vs Multiple Jobs)						
Lockdown	0.0214***	0.0214***	0.0156***	0.0136***	0.0136***	0.0135***	0.0134***
	(9.78)	(9.78)	(7.10)	(4.62)	(4.61)	(4.58)	(4.57)
Number of Observations	197784	197784	197784	197784	197784	197784	197784
	Outcome Variable: Working 35+ Hours Dummy						
Lockdown	-0.0671***	-0.0671***	-0.0502***	-0.0760***	-0.0760***	-0.0759***	-0.0757***
	(12.80)	(12.80)	(9.37)	(11.29)	(11.29)	(11.27)	(11.24)
Number of Observations	197784	197784	197784	197784	197784	197784	197784
	Outcome Variable: Working Hours (All Jobs)						
Lockdown	-2.287***	-2.287***	-1.115***	-2.513***	-2.511***	-2.509***	-2.502***
	(12.36)	(12.36)	(5.91)	(10.82)	(10.81)	(10.80)	(10.76)
Number of Observations	197784	197784	197784	197784	197784	197784	197784
	Outcome Variable: Working Hours (Main Job)						
Lockdown	-2.037***	-2.037***	-0.946***	-2.394***	-2.393***	-2.392***	-2.385***
	(11.26)	(11.26)	(5.11)	(10.48)	(10.48)	(10.47)	(10.44)
Number of Observations	197784	197784	197784	197784	197784	197784	197784
Person FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	No	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	Yes	Yes	Yes	Yes	Yes
Month FE	No	No	No	Yes	Yes	Yes	Yes
State*Year Inter	No	No	No	No	Yes	Yes	Yes
State*Month Inter	No	No	No	No	No	Yes	Yes
Demographic Controls	No	No	No	No	No	No	Yes

Notes: OLS regressions. Each panel-column displays estimates from a different regression. Lockdown is equal to 1 if the reference week is between 21 March 2020 and 31 May 2020 and 0 if reference week is between 1 January 2019 and 20 March 2020. Robust standard errors are clustered at the person-level. Absolute t-statistics are presented in parantheses. * , ** and *** indicate significance at the 10%, 5% and 1% level respectively.

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Appendix Table 3: Replacing State FE with Labour Market Region Fixed Effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Outcome Variable→	**In the Labour Force**		**Unemployed**		**Selfemployed (vs Employee)**		**Single Job (vs Multiple Jobs)**		**Working 35+ Hours Dummy**		**Working Hours (All Jobs)**		**Working Hours (Main Job)**	
Covid-19	-0.0206***		0.0119***		0.00174		0.00490		-0.0421***		-1.095***		-1.083***	
	(6.63)		(4.59)		(0.80)		(1.62)		(6.32)		(4.70)		(4.71)	
Lockdown		-0.0327***		0.0177***		0.00198		0.0134***		-0.0757***		-2.500***		-2.382***
		(10.16)		(6.69)		(0.95)		(4.55)		(11.22)		(10.74)		(10.40)
Number of Observations	277992	277992	206808	206808	196485	196485	196826	196826	196826	196826	196826	196826	196826	196826
Person FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Labour Market Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Labour Market Region*Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Labour Market Region*Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: OLS regressions. COVID-19 is equal to 1 if the reference week is between 11 March 2020 and 31 May 2020 and 0 if reference week is between 1 January 2019 and 10 March 2020. Lockdown is equal to 1 if the reference week is between 21 March 2020 and 31 May 2020 and 0 if reference week is between 1 January 2019 and 20 March 2020. There are 89 Labour Market Regions in Australia. Robust standard errors are clustered at the person-level. Absolute t-statistics are presented in parantheses. * , ** and *** indicate significance at the 10%, 5% and 1% level respectively.

Appendix Table 4: Regressions Using Population Weights

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Outcome Variable→	**In the Labour Force**		**Unemployed**		**Selfemployed (vs Employee)**		**Single Job (vs Multiple Jobs)**		**Working 35+ Hours Dummy**		**Working Hours (All Jobs)**		**Working Hours (Main Job)**	
Covid-19	-0.0209***		0.0124***		0.00205		0.00559*		-0.0402***		-1.158***		-1.122***	
	(6.11)		(4.58)		(0.95)		(1.68)		(5.87)		(4.97)		(4.90)	
Lockdown		-0.0327***		0.0180***		0.00203		0.0167***		-0.0718***		-2.599***		-2.450***
		(9.35)		(6.54)		(0.95)		(5.09)		(10.35)		(11.06)		(10.64)
Number of Observations	279368	279368	207803	207803	197443	197443	197784	197784	197784	197784	197784	197784	197784	197784
Person FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State*Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State*Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: OLS regressions. COVID-19 is equal to 1 if the reference week is between 11 March 2020 and 31 May 2020 and 0 if reference week is between 1 January 2019 and 10 March 2020. Lockdown is equal to 1 if the reference week is between 21 March 2020 and 31 May 2020 and 0 if reference week is between 1 January 2019 and 20 March 2020. Robust standard errors are clustered at the person-level. Absolute t-statistics are presented in parantheses. * , ** and *** indicate significance at the 10%, 5% and 1% level respectively.

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Appendix Table 5: Alternative Regression Samples

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Outcome Variable→	**In the Labour Force**		**Unemployed**		**Selfemployed (vs Employee)**		**Single Job (vs Multiple Jobs)**		**Working 35+ Hours Dummy**		**Working Hours (All Jobs)**		**Working Hours (Main Job)**	
	Panel A: 2016 January-2020 May													
Covid-19	-0.0142***		0.0112***		0.000192		0.00740***		-0.0767***		-2.654***		-2.577***	
	(7.33)		(6.86)		(0.15)		(4.21)		(17.36)		(17.09)		(16.84)	
Lockdown		-0.0280***		0.0196***		0.00192		0.0157***		-0.0696***		-2.924***		-2.748***
		(10.80)		(8.96)		(1.22)		(6.83)		(12.54)		(14.97)		(14.36)
Number of Observations	1287755	1287755	947524	947524	898152	898152	899799	899799	899799	899799	899799	899799	899799	899799
	Panel B: 2017 January-2020 May													
Covid-19	-0.0135***		0.0108***		0.000504		0.00742***		-0.0644***		-2.379***		-2.311***	
	(6.77)		(6.45)		(0.38)		(4.09)		(14.26)		(14.97)		(14.76)	
Lockdown		-0.0284***		0.0192***		0.00188		0.0157***		-0.0629***		-2.766***		-2.601***
		(10.82)		(8.66)		(1.17)		(6.74)		(11.18)		(14.01)		(13.44)
Number of Observations	958083	958083	708835	708835	672583	672583	673817	673817	673817	673817	673817	673817	673817	673817
	Panel C: 2018 January-2020 May													
Covid-19	-0.0126***		0.0107***		0.00106		0.00681***		-0.0408***		-1.339***		-1.286***	
	(5.96)		(6.01)		(0.73)		(3.48)		(8.55)		(7.97)		(7.77)	
Lockdown		-0.0277***		0.0185***		0.00203		0.0146***		-0.0641***		-2.416***		-2.274***
		(10.21)		(8.13)		(1.22)		(6.02)		(11.08)		(11.91)		(11.43)
Number of Observations	618744	618744	458967	458967	435893	435893	436680	436680	436680	436680	436680	436680	436680	436680
Person FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State*Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State*Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: OLS regressions. COVID-19 is equal to 1 if the reference week is between 11 March 2020 and 31 May 2020 and 0 if reference week is between 1 January 2019 and 10 March 2020. Lockdown is equal to 1 if the reference week is between 21 March 2020 and 31 May 2020 and 0 if reference week is between 1 January 2019 and 20 March 2020. Robust standard errors are clustered at the person-level. Absolute t-statistics are presented in parantheses. * , ** and *** indicate significance at the 10%, 5% and 1% level respectively.

Appendix Table 6: Interaction Effects with Categorical Job Tenure

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Outcome Variable→	**In the Labour Force**		**Unemployed**		**Selfemployed (vs Employee)**		**Single Job (vs Multiple Jobs)**		**Working 35+ Hours Dummy**		**Working Hours (All Jobs)**		**Working Hours (Main Job)**	
Covid-19	-0.0112**		0.00537**		0.000534		0.00251		-0.0227**		-0.253		-0.268	
	(2.55)		(2.31)		(0.16)		(0.58)		(2.06)		(0.64)		(0.68)	
Lockdown		-0.0177***		0.00539**		0.00531		0.00553		-0.0536***		-1.304**		-1.281**
		(3.07)		(2.12)		(1.41)		(1.08)		(3.83)		(2.52)		(2.50)
Covid-19/Lockdown*Tenure (1-3 months)	0.0203	-0.0203	-0.0263*	0.0147	-0.00671	-0.0206	0.00335	0.0510***	-0.0328	-0.0589*	-1.475**	-2.701**	-1.493**	-2.459**
	(1.30)	(0.89)	(1.76)	(0.62)	(0.57)	(1.19)	(0.27)	(3.00)	(1.44)	(1.84)	(2.04)	(2.36)	(2.13)	(2.23)
Covid-19/Lockdown*Tenure (4-6 months)	-0.00842	-0.0403**	0.0122	0.0282*	0.00132	-0.00787	-0.00337	0.000867	-0.0260	0.0120	-0.850	-0.381	-0.883	-0.436
	(0.79)	(2.31)	(1.23)	(1.89)	(0.19)	(0.81)	(0.35)	(0.06)	(1.31)	(0.43)	(1.42)	(0.43)	(1.53)	(0.52)
Covid-19/Lockdown*Tenure (7-11 months)	-0.0200*	-0.0253*	0.0253***	0.0442***	-0.00760	-0.00985	0.0117	0.00963	-0.0341*	-0.0313	-1.902***	-2.554**	-1.699**	-2.305**
	(1.94)	(1.74)	(2.84)	(2.83)	(0.94)	(0.82)	(1.05)	(0.81)	(1.73)	(1.09)	(2.75)	(2.46)	(2.48)	(2.23)
Covid-19/Lockdown*Tenure (1-5 years)	-0.0103**	-0.0179***	0.0102***	0.0159***	0.00148	-0.00553	0.00426	0.0113*	-0.0214*	-0.0303*	-1.043***	-1.464**	-1.013***	-1.328**
	(2.33)	(2.64)	(4.35)	(4.51)	(0.45)	(1.35)	(1.00)	(1.91)	(1.93)	(1.94)	(2.66)	(2.56)	(2.60)	(2.35)
Covid-19/Lockdown*Tenure (6-10 years)	-0.00429	-0.00255	0.00117	0.00595*	0.00202	-0.00297	-0.00176	0.00334	-0.0181	-0.0139	-0.435	-0.780	-0.479	-0.754
	(0.83)	(0.33)	(0.58)	(1.73)	(0.57)	(0.69)	(0.37)	(0.54)	(1.37)	(0.74)	(0.92)	(1.16)	(1.02)	(1.14)
Covid-19/Lockdown*Tenure (11-15 years)	-0.00286	0.00401	0.00113	0.00412	-0.00286	0.00148	-0.000830	0.00612	0.000132	-0.00681	0.135	-0.578	0.107	-0.481
	(0.52)	(0.51)	(0.39)	(0.93)	(0.67)	(0.30)	(0.17)	(0.90)	(0.01)	(0.32)	(0.27)	(0.79)	(0.21)	(0.66)
Number of Observations	191246	191246	185628	185628	183511	183511	183756	183756	183756	183756	183756	183756	183756	183756
Person FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State*Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State*Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: OLS regressions. COVID-19 is equal to 1 if the reference week is between 11 March 2020 and 31 May 2020 and 0 if reference week is between 1 January 2019 and 10 March 2020. Lockdown is equal to 1 if the reference week is between 21 March 2020 and 31 May 2020 and 0 if reference week is between 1 January 2019 and 20 March 2020. The reference category is Covid-19/Lockdown*Tenure (15+ years). The main effect of the interaction variable is included among the controls. Robust standard errors are clustered at the person-level. Absolute t-statistics are presented in parantheses. * , ** and *** indicate significance at the 10%, 5% and 1% level respectively.

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Appendix Table 7: Interaction Effects with Categorical Years Since Migration

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Outcome Variable→	**In the Labour Force**		**Unemployed**		**Selfemployed (vs Employee)**		**Single Job (vs Multiple Jobs)**		**Working 35+ Hours Dummy**		**Working Hours (All Jobs)**		**Working Hours (Main Job)**	
Covid-19	-0.0208***		0.00873***		0.00310		0.00485		-0.0384***		-1.011***		-0.984***	
	(6.35)		(3.25)		(1.39)		(1.51)		(5.48)		(4.12)		(4.07)	
Lockdown		-0.0310***		0.0124***		0.00310		0.0131***		-0.0681***		-2.296***		-2.193***
		(8.89)		(4.41)		(1.41)		(4.01)		(9.20)		(8.93)		(8.70)
Covid-19/Lockdown*0-9 Years since Migration	-0.00727	-0.0300**	0.0202**	0.0444***	-0.00738	-0.00803	0.00184	0.00298	-0.0422***	-0.0586***	-1.234**	-1.766**	-1.196**	-1.627**
	(0.84)	(2.50)	(2.48)	(3.58)	(1.45)	(1.24)	(0.27)	(0.31)	(2.82)	(2.76)	(2.46)	(2.45)	(2.45)	(2.33)
Covid-19/Lockdown*10-18 Years since Migration	0.0106	0.00758	0.00451	0.0108	-0.00544	0.00303	0.00642	0.00417	-0.0311**	-0.0466**	-1.069**	-1.651**	-1.063**	-1.512**
	(1.48)	(0.75)	(0.79)	(1.51)	(1.04)	(0.45)	(1.00)	(0.52)	(2.05)	(2.17)	(2.14)	(2.19)	(2.16)	(2.01)
Covid-19/Lockdown*19-34 Years since Migration	-0.0131**	-0.00969	0.00965*	0.00904	-0.00281	-0.00674	-0.00313	-0.00330	0.00617	-0.00501	0.548	0.131	0.384	0.0667
	(2.03)	(0.95)	(1.84)	(1.18)	(0.51)	(1.12)	(0.54)	(0.43)	(0.43)	(0.25)	(1.09)	(0.18)	(0.77)	(0.09)
Covid-19/Lockdown*35-70 Years since Migration	0.00562	0.00983	0.00928	0.00711	-0.00704	-0.00724	-0.00522	0.000748	0.0137	0.0109	0.562	0.759	0.501	0.712
	(0.89)	(1.07)	(1.37)	(0.69)	(1.15)	(0.96)	(0.90)	(0.09)	(0.84)	(0.47)	(0.99)	(0.97)	(0.89)	(0.92)
Number of Observations	279368	279368	207803	207803	197443	197443	197784	197784	197784	197784	197784	197784	197784	197784
Person FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State*Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State*Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: OLS regressions. COVID-19 is equal to 1 if the reference week is between 11 March 2020 and 31 May 2020 and 0 if reference week is between 1 January 2019 and 10 March 2020. Lockdown is equal to 1 if the reference week is between 21 March 2020 and 31 May 2020 and 0 if reference week is between 1 January 2019 and 20 March 2020. The reference category is Covid-19/Lockdown*Non-immigrant. The main effect of the interaction variable is included among the controls. Robust standard errors are clustered at the person-level. Absolute t-statistics are presented in parantheses. * , ** and *** indicate significance at the 10%, 5% and 1% level respectively.

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Appendix Table 8: Interaction Effects with Relationship in the Household

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Outcome Variable→	**In the Labour Force**	**Unemployed**	**Selfemployed (vs Employee)**	**Single Job (vs Multiple Jobs)**	**Working 35+ Hours Dummy**	**Working Hours (All Jobs)**	**Working Hours (Main Job)**
Panel A: Effects of COVID-19							
Covid-19	-0.0164***	0.0128***	0.00126	0.00592*	-0.0432***	-0.985***	-0.977***
	(5.04)	(4.73)	(0.53)	(1.86)	(5.99)	(3.87)	(3.89)
Covid-19*Head of Lone Parent Family	-0.0157*	-0.00542	0.00388	-0.00292	0.00369	0.698	0.795
	(1.84)	(0.95)	(0.73)	(0.37)	(0.21)	(1.25)	(1.43)
Covid-19*Children Aged 15+	-0.0138**	-0.00500	0.00260	0.00412	0.00116	-0.683**	-0.639**
	(2.21)	(0.88)	(0.72)	(0.79)	(0.11)	(2.11)	(2.02)
Covid-19*Living with Non-Relatives	-0.00870	0.00131	0.00105	-0.00247	0.0362	1.417*	1.407*
	(0.76)	(0.17)	(0.16)	(0.28)	(1.55)	(1.95)	(1.95)
Covid-19*Living Alone	-0.00761	0.00204	-0.00388	-0.0158**	-0.00986	-0.822*	-0.902**
	(1.56)	(0.38)	(1.10)	(2.53)	(0.72)	(1.79)	(2.00)
Covid-19*Relatives	-0.0306**	-0.00977	0.00117	0.0235	-0.0348	-2.607**	-2.348*
	(2.10)	(0.75)	(0.18)	(1.49)	(1.05)	(2.08)	(1.89)
Number of Observations	278681	207269	196926	197267	197267	197267	197267
Panel B: Effects of National Lockdown							
Lockdown	-0.0201***	0.0172***	0.00130	0.0110***	-0.0774***	-2.446***	-2.359***
	(5.88)	(6.12)	(0.54)	(3.42)	(9.99)	(8.95)	(8.79)
Lockdown*Head of Lone Parent Family	-0.0352***	-0.0118*	0.0119*	0.00983	-0.0127	0.499	0.738
	(2.96)	(1.79)	(1.78)	(0.96)	(0.53)	(0.62)	(0.93)
Lockdown*Children Aged 15+	-0.0460***	0.00373	0.00350	0.0136**	0.00470	-0.483	-0.487
	(5.18)	(0.44)	(0.85)	(2.10)	(0.33)	(1.03)	(1.07)
Lockdown*Living with Non-Relatives	-0.0336*	0.00259	-0.0122	0.00517	0.0194	0.829	0.944
	(1.90)	(0.23)	(1.12)	(0.40)	(0.56)	(0.85)	(0.97)
Lockdown*Living Alone	-0.0101	-0.000471	-0.00262	-0.00632	0.0132	0.122	0.235
	(1.48)	(0.07)	(0.61)	(0.70)	(0.70)	(0.18)	(0.36)
Lockdown*Relatives	-0.0602***	0.0210	0.000865	0.0496**	-0.0195	-3.907**	-3.690**
	(2.71)	(1.05)	(0.11)	(2.04)	(0.44)	(2.41)	(2.29)
Number of Observations	278681	207269	196926	197267	197267	197267	197267
Person FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State*Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State*Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: OLS regressions. COVID-19 is equal to 1 if the reference week is between 11 March 2020 and 31 May 2020 and 0 if reference week is between 1 January 2019 and 10 March 2020. Lockdown is equal to 1 if the reference week is between 21 March 2020 and 31 May 2020 and 0 if reference week is between 1 January 2019 and 20 March 2020. The reference category is Covid-19/Lockdown*Husband, Wife or Partner. The main effect of the interaction variable is included among the controls. Robust standard errors are clustered at the person-level. Absolute t-statistics are presented in parantheses. * , ** and *** indicate significance at the 10%, 5% and 1% level respectively.

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Appendix Table 9: Interaction Effects with Country of Birth

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Outcome Variable→	**In the Labour Force**		**Unemployed**		**Selfemployed (vs Employee)**		**Single Job (vs Multiple Jobs)**		**Working 35+ Hours Dummy**		**Working Hours (All Jobs)**		**Working Hours (Main Job)**	
Covid-19	-0.0215***		0.00907***		0.00257		0.00683**		-0.0398***		-1.114***		-1.054***	
	(6.43)		(3.29)		(1.16)		(2.08)		(5.55)		(4.42)		(4.24)	
Covid-19*Born in an English-Speaking Country	0.00498		0.00730		-0.00551		0.00190		-0.0121		0.0936		0.0815	
	(0.89)		(1.33)		(1.35)		(0.34)		(0.93)		(0.21)		(0.19)	
Covid-19*Born in a Non-English-Speaking Country	-0.0102*		0.0109**		-0.00399		-0.000996		-0.0142		-0.567		-0.625	
	(1.70)		(2.12)		(0.85)		(0.21)		(1.15)		(1.37)		(1.52)	
Lockdown		-0.0313***		0.0126***		0.00279		0.0143***		-0.0698***		-2.386***		-2.260***
		(8.89)		(4.45)		(1.26)		(4.34)		(9.32)		(9.15)		(8.84)
Lockdown*Born in an English-Speaking Country		0.0164*		0.0160**		-0.00818*		0.000872		-0.0185		0.0816		0.0999
		(1.96)		(1.99)		(1.69)		(0.12)		(0.99)		(0.13)		(0.16)
Lockdown*Born in a Non-English-Speaking Country		-0.0318***		0.0151**		-0.00221		0.00135		-0.0379**		-1.318**		-1.204*
		(3.57)		(2.00)		(0.38)		(0.19)		(2.09)		(2.06)		(1.91)
Number of Observations	260542	260542	193231	193231	183706	183706	184033	184033	184033	184033	184033	184033	184033	184033
Person FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State*Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State*Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: OLS regressions. COVID-19 is equal to 1 if the reference week is between 11 March 2020 and 31 May 2020 and 0 if reference week is between 1 January 2019 and 10 March 2020. Lockdown is equal to 1 if the reference week is between 21 March 2020 and 31 May 2020 and 0 if reference week is between 1 January 2019 and 20 March 2020. The reference category is Covid-19/Lockdown*Born in Australia. The main effect of the interaction variable is included among the controls. Robust standard errors are clustered at the person-level. Absolute t-statistics are presented in parantheses. * , ** and *** indicate significance at the 10%, 5% and 1% level respectively.

Appendix Table 10: Interaction Effects with Occupational Skill Level

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Outcome Variable→	**In the Labour Force**		**Unemployed**		**Selfemployed (vs Employee)**		**Single Job (vs Multiple Jobs)**		**Working 35+ Hours Dummy**		**Working Hours (All Jobs)**		**Working Hours (Main Job)**	
Covid-19	-0.00754*		0.0124***		0.00150		0.00299		-0.00883		0.782***		0.826***	
	(1.92)		(4.28)		(0.57)		(0.78)		(1.04)		(2.69)		(2.88)	
Lockdown		-0.0102**		0.0101***		0.000554		0.00838**		-0.0281***		0.0163		0.113
		(2.42)		(3.39)		(0.19)		(2.01)		(2.94)		(0.05)		(0.35)
Covid-19/Lockdown*Occupational Skill Level 1	-0.0179***	-0.0431***	0.00436	0.0202***	-0.00413	-0.00280	0.00299	0.00665	-0.0256**	-0.0424***	-2.862***	-3.702***	-2.934***	-3.669***
	(2.75)	(4.59)	(0.85)	(2.69)	(1.12)	(0.59)	(0.57)	(0.99)	(2.40)	(2.79)	(7.78)	(6.85)	(8.08)	(6.90)
Covid-19/Lockdown*Occupational Skill Level 2	-0.0120**	-0.0286***	-0.000543	0.00841	-0.000128	0.00116	0.00236	0.0105*	-0.0311***	-0.0485***	-1.963***	-2.873***	-2.032***	-2.851***
	(2.52)	(4.04)	(0.15)	(1.61)	(0.04)	(0.31)	(0.53)	(1.69)	(3.08)	(3.54)	(5.73)	(5.95)	(6.07)	(6.05)
Covid-19/Lockdown*Occupational Skill Level 3	-0.0156***	-0.0239***	0.00188	0.0183***	0.00180	0.00557	-0.000995	-0.0000800	-0.0712***	-0.0950***	-3.503***	-4.440***	-3.564***	-4.458***
	(2.80)	(3.04)	(0.45)	(2.83)	(0.43)	(1.03)	(0.21)	(0.01)	(5.89)	(5.72)	(8.53)	(7.76)	(8.81)	(7.87)
Covid-19/Lockdown*Occupational Skill Level 4	-0.0130**	-0.0223***	0.000576	0.00534	0.00159	0.00757*	0.00615	0.00530	-0.0571***	-0.0688***	-2.799***	-3.586***	-2.787***	-3.540***
	(2.51)	(2.77)	(0.14)	(0.85)	(0.42)	(1.68)	(1.38)	(0.86)	(4.51)	(3.74)	(6.67)	(5.58)	(6.76)	(5.68)
Number of Observations	206022	206022	198347	198347	192313	192313	192587	192587	192587	192587	192587	192587	192587	192587
Person FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State*Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State*Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: OLS regressions. COVID-19 is equal to 1 if the reference week is between 11 March 2020 and 31 May 2020 and 0 if reference week is between 1 January 2019 and 10 March 2020. Lockdown is equal to 1 if the reference week is between 21 March 2020 and 31 May 2020 and 0 if reference week is between 1 January 2019 and 20 March 2020. Occupational Skills are defined in terms of formal education, training, previous experience and on-the-job training by the ABS. Higher values are associated with higher occupational skill. The reference category is Covid-19/Lockdown*Occupational Skill Level 5. The main effect of the interaction variable is included among the controls. Robust standard errors are clustered at the person-level. Absolute t-statistics are presented in parantheses. * , ** and *** indicate significance at the 10%, 5% and 1% level respectively.

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Appendix Table 11: Interaction Effects of Covid-19 with Main Field of Qualification

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Outcome Variable→	**In the Labour Force**	**Unemployed**	**Selfemployed (vs Employee)**	**Single Job (vs Multiple Jobs)**	**Working 35+ Hours Dummy**	**Working Hours (All Jobs)**	**Working Hours (Main Job)**
Covid-19	-0.0263***	0.0120***	0.00138	0.00477	-0.0579***	-2.075***	-2.125***
	(6.50)	(3.25)	(0.52)	(1.24)	(6.81)	(7.06)	(7.32)
Covid-19*No Qualification	0.0663***	0.0325	0.00368	0.00819	0.0591	1.344	1.375
	(2.67)	(0.89)	(1.62)	(0.39)	(1.00)	(0.64)	(0.68)
Covid-19*Natural and Physical Sciences	0.00418	0.0182**	-0.00283	0.00612	0.0201	1.511**	1.608**
	(0.38)	(1.98)	(0.37)	(0.60)	(0.87)	(1.97)	(2.12)
Covid-19*Information Technology	0.0140	0.0164*	0.0102	0.00370	0.0273	1.749***	1.776***
	(1.44)	(1.67)	(1.36)	(0.52)	(1.28)	(2.68)	(2.74)
Covid-19*Engineering	0.00280	0.00357	0.00369	-0.0106**	0.000506	0.839*	0.861*
	(0.53)	(0.69)	(1.03)	(2.32)	(0.04)	(1.80)	(1.86)
Covid-19*Architecture and Building	0.000878	0.00481	0.00143	0.00871	0.00620	0.788	0.907
	(0.11)	(0.65)	(0.16)	(1.12)	(0.29)	(1.02)	(1.19)
Covid-19*Agriculture and Enviromental Studies	0.0307**	-0.0160**	-0.0140	-0.0181	-0.0196	0.686	0.740
	(2.24)	(2.21)	(1.24)	(1.48)	(0.59)	(0.54)	(0.59)
Covid-19*Health	0.0135*	-0.00458	0.00467	-0.0130*	0.0418***	2.229***	2.209***
	(1.83)	(0.89)	(0.95)	(1.81)	(2.82)	(4.51)	(4.55)
Covid-19*Education	0.0202**	-0.0111*	-0.00205	-0.00571	0.105***	5.549***	5.555***
	(2.52)	(1.90)	(0.40)	(0.76)	(6.84)	(9.45)	(9.49)
Covid-19*Management and Commerce	0.0185***	0.000909	0.00140	-0.00155	0.0362***	1.840***	1.857***
	(3.32)	(0.18)	(0.35)	(0.30)	(3.15)	(4.75)	(4.96)
Covid-19*Society and Culture	-0.00204	-0.00517	-0.000409	0.00587	0.0251*	1.057**	1.178**
	(0.30)	(1.00)	(0.10)	(0.94)	(1.72)	(2.22)	(2.53)
Covid-19*Creative Arts	-0.0111	-0.00769	-0.00111	0.0253**	-0.0216	0.122	0.573
	(0.92)	(0.82)	(0.13)	(1.99)	(0.93)	(0.16)	(0.80)
Covid-19*Food, Hospitality and Personal Services	-0.00757	0.00618	-0.00650	0.0272**	-0.0822***	-3.350***	-2.965***
	(0.72)	(0.64)	(0.75)	(2.54)	(3.68)	(4.54)	(4.05)
Number of Observations	275074	204508	194318	194645	194645	194645	194645
Person FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State*Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State*Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: OLS regressions.COVID-19 is equal to 1 if the reference week is between 11 March 2020 and 31 May 2020 and 0 if reference week is between 1 January 2019 and 10 March 2020. The reference category is Covid-19*Mixed Field Programmes. The main effect of the interaction variable is included among the controls. Education variables are excluded from these regressions as controls. Mixed Field Programmes are programmes providing general and personal development education such as literacy and numeracy skills, personal, social and workplace relationships. Robust standard errors are clustered at the person-level. Absolute t-statistics are presented in parantheses. * , ** and *** indicate significance at the 10%, 5% and 1% level respectively.

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Appendix Table 12: Interaction Effects of National Lockdown with Main Field of Qualification

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Outcome Variable→	**In the Labour Force**	**Unemployed**	**Selfemployed (vs Employee)**	**Single Job (vs Multiple Jobs)**	**Working 35+ Hours Dummy**	**Working Hours (All Jobs)**	**Working Hours (Main Job)**
Lockdown	-0.0482***	0.0181***	0.00151	0.0130***	-0.0886***	-3.365***	-3.343***
	(9.71)	(3.93)	(0.55)	(3.10)	(8.79)	(9.54)	(9.62)
Lockdown*No Qualification	0.0345**	0.0739	0.00238	-0.00400	-0.0109	1.607	1.535
	(2.38)	(0.86)	(0.91)	(0.23)	(0.18)	(0.77)	(0.76)
Lockdown*Natural and Physical Sciences	0.0265*	0.0207	-0.00766	0.0125	0.0577*	2.747***	2.895***
	(1.90)	(1.23)	(1.18)	(0.78)	(1.77)	(2.67)	(2.83)
Lockdown*Information Technology	0.0296**	0.0132	0.000608	-0.00190	0.0605**	3.202***	3.133***
	(2.22)	(0.90)	(0.06)	(0.21)	(2.21)	(3.39)	(3.35)
Lockdown*Engineering	0.0239***	0.00373	0.000696	-0.0127*	-0.00605	0.850	0.994
	(3.21)	(0.51)	(0.19)	(1.95)	(0.33)	(1.34)	(1.58)
Lockdown*Architecture and Building	0.0162	0.000651	-0.00213	0.00655	-0.0111	0.995	1.228
	(1.33)	(0.06)	(0.17)	(0.62)	(0.37)	(0.94)	(1.18)
Lockdown*Agriculture and Enviromental Studies	0.0675***	-0.0197**	-0.00551	-0.0139	-0.0470	0.885	0.918
	(4.93)	(2.10)	(0.34)	(0.63)	(1.03)	(0.54)	(0.57)
Lockdown*Health	0.0370***	-0.0106*	0.00878	-0.00247	0.0598***	2.532***	2.618***
	(3.84)	(1.70)	(1.56)	(0.28)	(3.00)	(3.57)	(3.81)
Lockdown*Education	0.0378***	-0.0113	-0.00575	0.00629	0.0671***	3.568***	3.648***
	(3.42)	(1.20)	(0.86)	(0.56)	(3.07)	(4.22)	(4.32)
Lockdown*Management and Commerce	0.0390***	-0.00184	0.00561	-0.00882	0.0370**	2.149***	2.133***
	(5.07)	(0.26)	(1.06)	(1.24)	(2.30)	(3.93)	(3.98)
Lockdown*Society and Culture	0.0151	-0.00546	-0.00282	0.00932	0.0341*	1.170*	1.351**
	(1.62)	(0.76)	(0.52)	(1.19)	(1.70)	(1.71)	(2.03)
Lockdown*Creative Arts	-0.000819	0.00130	-0.000106	0.0354**	-0.0193	-0.688	-0.152
	(0.04)	(0.10)	(0.01)	(1.97)	(0.65)	(0.66)	(0.16)
Lockdown*Food, Hospitality and Personal Services	-0.0162	0.0140	0.00219	0.0234	-0.142***	-7.226***	-6.625***
	(1.05)	(1.08)	(0.21)	(1.58)	(4.39)	(6.05)	(5.65)
Number of Observations	275074	204508	194318	194645	194645	194645	194645
Person FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State*Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State*Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: OLS regressions. Lockdown is equal to 1 if the reference week is between 21 March 2020 and 31 May 2020 and 0 if reference week is between 1 January 2019 and 20 March 2020. The reference category is Lockdown*Mixed Field Programmes. The main effect of the interaction variable is included among the controls. Highest education completed variables are excluded from these regressions as controls. Mixed Field Programmes are programmes providing general and personal development education such as literacy and numeracy skills, personal, social and workplace relationships. Robust standard errors are clustered at the person-level. Absolute t-statistics are presented in parantheses. * , ** and *** indicate significance at the 10%, 5% and 1% level respectively.

Appendix Table 13: Interaction Effects with 1-Digit Occupation Groups

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Outcome Variable→	**In the Labour Force**		**Unemployed**		**Selfemployed (vs Employee)**		**Single Job (vs Multiple Jobs)**		**Working 35+ Hours Dummy**		**Working Hours (All Jobs)**		**Working Hours (Main Job)**	
Covid-19	-0.00981**		0.0174***		0.00163		0.00861*		-0.0637***		-1.723***		-1.701***	
	(2.00)		(4.13)		(0.45)		(1.88)		(5.27)		(3.93)		(3.91)	
Lockdown		-0.0183***		0.0151***		0.00115		0.0109*		-0.109***		-3.066***		-3.024***
		(2.99)		(3.12)		(0.25)		(1.94)		(6.84)		(5.12)		(5.08)
Covid-19/Lockdown*Professionals	0.00157	0.00797	-0.00838**	-0.00667	0.00146	0.00109	-0.00801	-0.00297	0.0655***	0.0914***	3.063***	3.435***	3.061***	3.477***
	(0.30)	(1.11)	(1.98)	(1.24)	(0.38)	(0.21)	(1.59)	(0.43)	(5.04)	(5.02)	(6.67)	(5.18)	(6.75)	(5.29)
Covid-19/Lockdown*Technicians and Trade Workers	-0.0176***	-0.0224**	-0.00401	0.00846	0.000204	0.00453	-0.00462	-0.00112	-0.0140	-0.0171	-0.640	-1.053	-0.630	-0.931
	(2.84)	(2.47)	(0.78)	(1.12)	(0.04)	(0.77)	(0.90)	(0.16)	(0.91)	(0.79)	(1.20)	(1.35)	(1.19)	(1.21)
Covid-19/Lockdown*Community and Professional Service Workers	-0.0270***	-0.0719***	-0.00115	0.0228**	0.00137	0.00544	0.00509	0.0285***	0.0270*	0.0249	-0.661	-2.452***	-0.548	-2.088**
	(3.49)	(5.66)	(0.18)	(2.21)	(0.32)	(0.91)	(0.75)	(2.67)	(1.80)	(1.17)	(1.23)	(2.95)	(1.04)	(2.55)
Covid-19/Lockdown*Clerical and Administrative Workers	0.00767	0.0155*	-0.00989*	-0.00838	-0.000734	-0.00115	-0.00251	0.00366	0.0366**	0.0805***	1.578***	2.530***	1.587***	2.589***
	(1.34)	(1.96)	(1.85)	(1.25)	(0.16)	(0.19)	(0.48)	(0.48)	(2.56)	(4.04)	(3.31)	(3.66)	(3.37)	(3.80)
Covid-19/Lockdown*Sales Workers	-0.0150*	-0.0242**	-0.00109	0.0126	0.00255	0.00145	-0.00667	-0.00178	0.0173	0.0302	-0.620	-0.543	-0.724	-0.520
	(1.82)	(2.04)	(0.17)	(1.39)	(0.55)	(0.23)	(0.95)	(0.21)	(1.18)	(1.41)	(1.20)	(0.69)	(1.43)	(0.67)
Covid-19/Lockdown*Machinery Operators and Drivers	-0.0156*	-0.0167	-0.00804	0.00503	-0.00240	0.00127	-0.0141*	-0.0144	-0.0160	-0.0225	-0.480	-1.114	-0.721	-1.384
	(1.78)	(1.29)	(1.19)	(0.51)	(0.36)	(0.16)	(1.92)	(1.58)	(0.77)	(0.79)	(0.58)	(0.98)	(0.89)	(1.24)
Covid-19/Lockdown*Labourers	-0.0188**	-0.0430***	0.000917	0.0129	-0.00961*	-0.0117*	-0.00345	0.00564	0.0191	0.0271	0.145	0.364	0.0350	0.364
	(2.19)	(3.30)	(0.13)	(1.27)	(1.81)	(1.73)	(0.55)	(0.57)	(1.17)	(1.12)	(0.25)	(0.42)	(0.06)	(0.43)
Number of Observations	206557	206557	198832	198832	192776	192776	193053	193053	193053	193053	193053	193053	193053	193053

Notes: OLS regressions. COVID-19 is equal to 1 if the reference week is between 11 March 2020 and 31 May 2020 and 0 if reference week is between 1 January 2019 and 10 March 2020. Lockdown is equal to 1 if the reference week is between 21 March 2020 and 31 May 2020 and 0 if reference week is between 1 January 2019 and 20 March 2020. Lockdown is a dummy variable which takes the value 1 if a person is interviewed on or after the 22nd of March and 0 if a person is interviewed before that date. The reference category is Covid-19/Lockdown*Managers and Administrators. All regressions include demographic controls, person fe, state fe, year fe, month fe, state by year fe, state by month as well as the main effect of the interaction variable. Robust standard errors are clustered at the person-level. Absolute t-statistics are presented in parantheses. * , ** and *** indicate significance at the 10%, 5% and 1% level respectively.

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Appendix Table 14: Interaction Effects with 1-Digit Industry Groups

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Outcome Variable→	**In the Labour Force**		**Unemployed**		**Selfemployed (vs Employee)**		**Single Job (vs Multiple Jobs)**		**Working 35+ Hours Dummy**		**Working Hours (All Jobs)**		**Working Hours (Main Job)**	
Covid-19	0.00138		0.0200**		-0.00732		0.00266		-0.0486**		-2.098**		-2.053**	
	(0.14)		(2.17)		(0.85)		(0.27)		(2.10)		(2.50)		(2.42)	
Lockdown		0.0106		0.0167		-0.0203*		-0.00698		-0.0553*		-1.022		-1.129
		(0.74)		(1.44)		(1.69)		(0.45)		(1.94)		(0.97)		(1.04)
Covid-19/Lockdown*Mining	-0.0164	-0.0178	0.0122	0.0239	0.0114	0.0295**	-0.00980	-0.00591	0.0248	0.0686	1.214	1.653	0.738	1.149
	(1.16)	(0.98)	(0.81)	(1.05)	(1.10)	(2.35)	(0.68)	(0.27)	(0.66)	(1.45)	(0.64)	(0.73)	(0.40)	(0.52)
Covid-19/Lockdown*Manufacturing	-0.0107	-0.0175	-0.00949	-0.00519	0.00614	0.0199	-0.00343	0.0205	-0.0224	-0.0503	0.748	-1.000	0.649	-0.751
	(0.92)	(1.04)	(0.98)	(0.41)	(0.67)	(1.59)	(0.33)	(1.20)	(0.84)	(1.44)	(0.80)	(0.80)	(0.69)	(0.59)
Covid-19/Lockdown*Electricity, Gas Services	-0.00476	-0.00333	-0.0202*	-0.0212	0.00932	0.0168	0.00340	0.0116	-0.0536	-0.0371	-1.180	-1.926	-1.294	-1.906
	(0.30)	(0.15)	(1.92)	(1.56)	(0.73)	(0.87)	(0.28)	(0.69)	(1.23)	(0.61)	(0.81)	(0.93)	(0.89)	(0.91)
Covid-19/Lockdown*Construction	-0.0106	-0.0212	-0.00430	0.0132	0.00556	0.0215	-0.00212	0.00995	-0.0163	-0.0169	0.988	-0.554	0.950	-0.394
	(0.94)	(1.32)	(0.41)	(0.91)	(0.57)	(1.59)	(0.20)	(0.60)	(0.62)	(0.50)	(1.05)	(0.46)	(1.00)	(0.32)
Covid-19/Lockdown*Wholesale Trade	-0.0260*	-0.0463**	-0.0192*	-0.0129	0.00590	0.0280**	-0.00180	0.0120	-0.0123	-0.0264	0.374	-1.016	0.163	-0.874
	(1.89)	(2.28)	(1.86)	(0.92)	(0.62)	(1.99)	(0.16)	(0.66)	(0.40)	(0.64)	(0.35)	(0.74)	(0.16)	(0.64)
Covid-19/Lockdown*Retail Trade	-0.0244**	-0.0528***	-0.00536	0.000192	0.0121	0.0245*	0.00196	0.0153	0.00187	-0.0361	-0.199	-3.336***	-0.262	-3.143***
	(2.09)	(3.05)	(0.52)	(0.01)	(1.35)	(1.96)	(0.18)	(0.94)	(0.08)	(1.12)	(0.22)	(2.82)	(0.29)	(2.60)
Covid-19/Lockdown*Accommodation Services	-0.0561***	-0.144***	0.0138	0.0472**	0.0121	0.0284**	0.0157	0.0396**	-0.0465*	-0.169***	-2.584***	-10.21***	-2.517***	-9.794***
	(4.00)	(6.55)	(1.14)	(2.54)	(1.26)	(2.18)	(1.31)	(2.17)	(1.76)	(4.61)	(2.70)	(7.06)	(2.62)	(6.70)
Covid-19/Lockdown*Transport, Postal, Warehousing	-0.0237*	-0.0569***	-0.00511	0.00723	0.0116	0.0261*	-0.00976	0.0106	-0.0170	-0.0997***	-0.153	-3.979***	-0.270	-3.695**
	(1.87)	(2.91)	(0.44)	(0.48)	(1.01)	(1.75)	(0.86)	(0.59)	(0.59)	(2.61)	(0.14)	(2.76)	(0.25)	(2.54)
Covid-19/Lockdown*Information and Telecommunications	-0.0116	-0.0339	-0.0164	-0.0190	0.00941	0.0243*	-0.0104	0.000453	-0.00110	0.0538	1.579	1.225	1.516	1.047
	(0.79)	(1.57)	(1.61)	(1.35)	(0.84)	(1.87)	(0.82)	(0.02)	(0.03)	(1.12)	(1.34)	(0.71)	(1.28)	(0.61)
Covid-19/Lockdown*Financial and Insurance Services	-0.00597	-0.0237	-0.0130	-0.00556	0.0123	0.0200	0.00194	0.0186	-0.0242	0.0309	1.880*	2.138*	1.790*	2.178*
	(0.46)	(1.29)	(1.22)	(0.38)	(1.12)	(1.53)	(0.16)	(1.04)	(0.79)	(0.80)	(1.86)	(1.71)	(1.79)	(1.71)
Covid-19/Lockdown*Real Estate Services	-0.0344**	-0.0431**	0.000188	-0.00110	0.0217	0.0340	0.0168	0.0390*	-0.0468	-0.0948*	-0.137	-2.597	-0.0759	-2.313
	(1.96)	(2.06)	(0.02)	(0.07)	(1.32)	(1.50)	(0.99)	(1.76)	(1.28)	(1.85)	(0.11)	(1.50)	(0.06)	(1.35)
Covid-19/Lockdown*Professional, Scientific, Technical Services	-0.0122	-0.0314*	-0.00313	0.00330	0.00289	0.0225	0.00771	0.0194	0.0181	0.00756	1.735*	-0.0321	1.776*	0.159
	(1.10)	(1.88)	(0.31)	(0.25)	(0.30)	(1.60)	(0.68)	(1.14)	(0.70)	(0.23)	(1.92)	(0.03)	(1.96)	(0.13)
Covid-19/Lockdown*Administrative Services	-0.0443***	-0.0558**	0.00160	0.0259	-0.0154	0.000373	0.0207	0.0448*	-0.000771	-0.0780*	-0.358	-3.423**	-0.323	-3.281**
	(2.72)	(2.54)	(0.12)	(1.24)	(1.08)	(0.02)	(1.36)	(1.82)	(0.03)	(1.91)	(0.34)	(2.33)	(0.31)	(2.30)
Covid-19/Lockdown*Public Administration and Safety	-0.0109	-0.0234	-0.0177*	-0.0148	0.0126	0.0236*	-0.00389	0.00884	0.0542**	0.0625*	2.920***	1.995*	2.885***	2.173*
	(1.00)	(1.52)	(1.80)	(1.19)	(1.44)	(1.93)	(0.38)	(0.56)	(2.04)	(1.87)	(3.11)	(1.67)	(3.06)	(1.79)
Covid-19/Lockdown*Education	-0.00175	-0.0183	-0.00759	-0.00297	0.00889	0.0175	0.00161	0.0307*	0.0900***	0.0535	5.101***	1.552	5.048***	1.836
	(0.15)	(1.12)	(0.78)	(0.23)	(0.98)	(1.36)	(0.14)	(1.70)	(3.55)	(1.64)	(5.56)	(1.30)	(5.46)	(1.50)
Covid-19/Lockdown*Health Care	-0.0130	-0.0257*	-0.0155	-0.00976	0.0125	0.0252**	-0.00416	0.0178	0.0415*	0.0363	1.991**	0.137	1.876**	0.340
	(1.21)	(1.67)	(1.64)	(0.80)	(1.44)	(2.06)	(0.39)	(1.08)	(1.70)	(1.17)	(2.28)	(0.12)	(2.13)	(0.29)
Covid-19/Lockdown*Arts and Recreation Services	-0.0744***	-0.191***	-0.00363	0.0156	0.00472	0.0130	0.0342**	0.0499**	-0.118***	-0.267***	-3.321***	-10.82***	-2.897**	-10.12***
	(3.37)	(5.07)	(0.20)	(0.52)	(0.40)	(0.79)	(2.05)	(1.98)	(3.17)	(4.82)	(2.58)	(5.48)	(2.27)	(5.22)
Covid-19/Lockdown*Other Services	-0.0396***	-0.0911***	-0.00951	0.00214	0.00769	0.0220	0.0107	0.0388**	-0.00735	-0.0823**	-0.237	-5.320***	-0.0801	-4.926***
	(2.77)	(4.24)	(0.82)	(0.14)	(0.75)	(1.60)	(0.88)	(2.02)	(0.25)	(2.05)	(0.23)	(3.63)	(0.08)	(3.33)
Number of Observations	206557	206557	198832	198832	192776	192776	193053	193053	193053	193053	193053	193053	193053	193053

Notes: OLS regressions. COVID-19 is equal to 1 if the reference week is between 11 March 2020 and 31 May 2020 and 0 if reference week is between 1 January 2019 and 10 March 2020. Lockdown is equal to 1 if the reference week is between 21 March 2020 and 31 May 2020 and 0 if reference week is between 1 January 2019 and 20 March 2020. Lockdown is a dummy variable which takes the value 1 if a person is interviewed on or after the 22nd of March and 0 if a person is interviewed before that date. The reference category is Covid-19/Lockdown*Agriculture, Forestry and Fishing. All regressions include demographic controls, person fe, state fe, year fe, month fe, state by year fe, state by month as well as the main effect of the interaction variable. Robust standard errors are clustered at the person-level. Absolute t-statistics are presented in parantheses. * , ** and *** indicate significance at the 10%, 5% and 1% level respectively.

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Appendix Table 15: Lockdown and Expectations about Future Employment among the Employed

	(1)	(2)
Outcome Variable→	**Expect to Remain Working for the Current Employer in the next 12 Months**	**Expect to Continue to be Employed in the next 12 Months**
Lockdown (Covid-19)	0.0122*	0.00493
	(1.78)	(1.15)
Person FE	Yes	Yes
Demographic Controls	Yes	Yes
State FE	Yes	Yes
Year FE	Yes	Yes
Month FE	Yes	Yes
State*Year FE	Yes	Yes
State*Month FE	Yes	Yes
Number of Observations	66907	66907

Notes: OLS regressions. Lockdown is equal to 1 if the reference week is between 21 March 2020 and 31 May 2020 and 0 if reference week is between 1 January 2019 and 20 March 2020. This question is asked only to individuals who are employed. The ABS asks expectations about future employment only to employed respondents only in February, May, August and November of every year. *Expect to Remain Working for the Current Employer* is a dummy variable equal to 1 if the respondent expects to stay in the same occupation or in own business in twelve months and 0 if the respondent doesn't expect to be working in the same job, expects to work on a seasonal, temporary, fixed term or causal job, expects to seek employment, retire, return to study or finish work for other reasons. *Expect to Continue to be Employed* is a dummy variable equal to one if the respondent expects to be employed either in the same job or in another and zero if the respondent expects to be retired, return to studying, or finish work for other reasons. Robust standard errors are clustered at the person-level. Absolute t-statistics are presented in parantheses. * , ** and *** indicate significance at the 10%, 5% and 1% level respectively.

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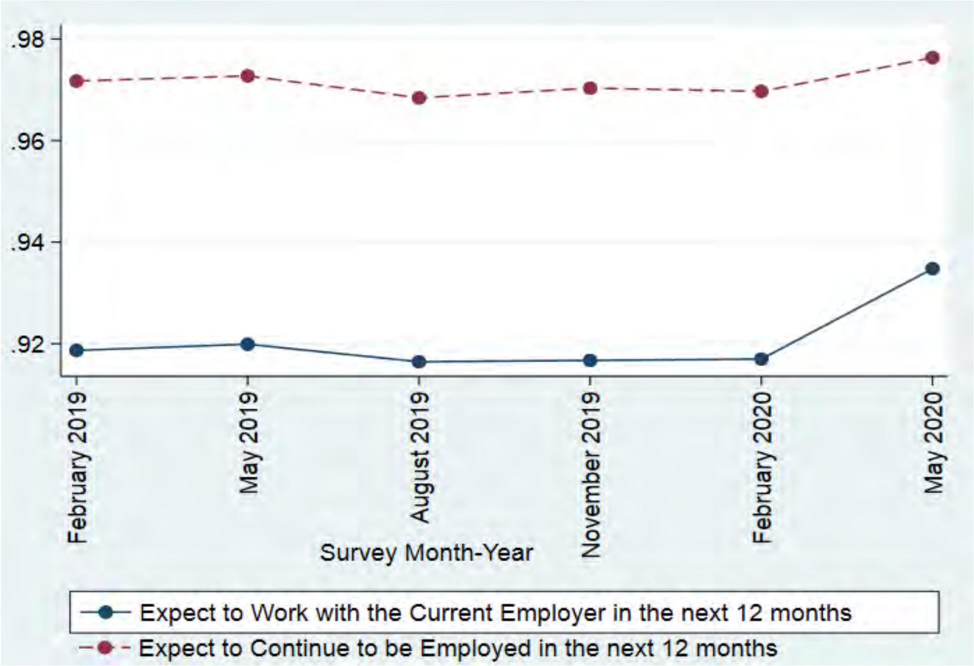
Appendix Figure 1: Evolution of Employment Expectatations over Time



Appendix Table 16: Did Respondents Correctly Predict Their Employement Status According to Their Expectations before the Lockdown?

Expect to Work in the next 12 months	Working		
	No	**Yes**	**Total**
No	71	394	465
	15.27%	84.73%	100%
Yes	757	14,657	15,414
	4.91%	95.09%	100%
Total	828	15,051	15,879

Notes: *Expect to work in the next twelve months* variable is measured in February 2020 before the lockdown and the pandemic decleration while *working* variable is measured in March, April and May 2020. The % numbers are raw percentages.

The long-term economic cost of Covid-19 in the Consensus Forecasts

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Date submitted: 9 August 2020; Date accepted: 19 August 2020

This note evaluates the expected economic toll of the Covid-19 pandemic in the Consensus Forecast surveys. It employs the surveys' forecasts at different horizons. Its main findings are as follows. First, the recovery is expected to be neither U- nor V-shaped but ``akin to a lopsided square root sign'' (Tett (2020)). Second, because the recovery is slow and incomplete, GDP losses during the Lockdown represent a small fraction of the total GDP loss, expected to reach 3 to 4% per annum for the developed countries under review. Third, there are massive differences in the economic toll among countries, which are only partly explained by their public-health performances.

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1 DPA Risk Premiums

1 Introduction

The evaluation of the economic cost of the Covid-19 pandemic is still a work in progress. Initial estimates from the OECD (2020) in March 2020 and the IMF (2020*a*) in April erred on the side of significantly underestimating the pandemic toll and were subsequently revised.

Against this rapidly-evolving backdrop, higher-frequency GDP forecasts, such as the monthly *Consensus Forecasts*, may provide a more timely gauge. Admittedly, surveys often react slowly after structural changes or large shocks in foreign countries (see Batchelor (2007), Dovern & Weisser (2011) and Loungani & Tamirisa (2011)). But this slowness is probably less apparent during the current pandemic which has been the focus of an enormous body of economic literature. Therefore, the assessment by the Consensus Forecasts (CF) survey of the cost of the pandemic provides a relevant and useful information.

The cost of the pandemic will depend on the shape of the ongoing recovery which the alphabet-soup of Roman letters (U, V, L, W...) seems unable to depict. In the Financial Times, Tett (2020) suggested to capture it instead with the "bank" symbol in Pitman shorthand, "akin to a lopsided square root sign", as central banks' actions can arguably bolster equity markets but but not foster sustainable growth. Obviously, this raises the issue of the efficacy of monetary policy at the zero-lower bound (see Woodford (2012)) which is beyond the scope of this note.

Ms. Tett's comments on the shape of the recovery echo a point made in the IMF's World Economic Outlook in June 2020 (see IMF (2020*b*)). The IMF forecasts suggest that the Covid-19 pandemic may cause long-term GDP losses. While the Chinese economy is expected to revert back to its pre-Covid-19 path, developed economies are not. More precisely, the IMF forecasts that GDP growth will resume at its previous pace but that, in level terms, GDP will remain lower than previously anticipated. Should these forecasts prove correct, the pandemic will have a long-lasting cost.

Against this background, this note shows that private-sector forecasters in the CF survey share the same conclusions. Combining the survey's annual projections with its long-term forecasts, it finds that forecasters currently anticipate an incomplete recovery from the pandemic. While GDP *growth* is expected to revert back to its previous pace by 2022 or 2023, GDP *levels* would remain below their pre-pandemic expected trajectory. For the countries under review, the average cumulative loss between 2020 to 2025 amounts to almost 4% per annum. The initial GDP meltdown during the Lockdown represents only a small fraction of this amount. Also, all countries are not equal in their ability to cope with the pandemic, and Sweden or Switzerland are expected to significantly outperform, say, Spain or Italy.

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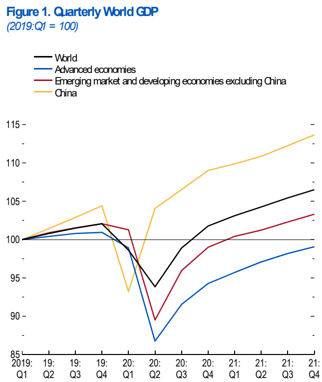
Figure 1: Imperfect recovery from the Covid-19 crisis



Source: IMF (2020*b*)

2 A basic framework

Since developed economies have been buffeted by the pandemic, forecasters have had to jettison their macroeconometric models which failed to capture this unusual combination of supply and demand shocks.

Standard macroeconomic models encountered theoretical and statistical hurdles to describe the impact of the pandemic. On the theoretical front, the economic outlook depends on the relative importance of demand and supply shocks and on their interaction. As Guerrieri et al. (2020) emphasize, under certain conditions, possibly met by the Covid-19 pandemic, supply shocks may trigger larger demand shocks in the short run, causing what they called "Keynesian supply shocks". But standard macroeconomic models do not describe well these unusually severe disruptions of labor markets or waves of bankruptcies. They are also ill-equipped to analyze some potential long-run consequences of the pandemic, from changes in saving behaviors to the worldwide reorganization of supply chains.

The economic analysis of the pandemic has also been plagued with statistical issues. The timing of the lockdown, around mid-March in many countries, meant that monthly indicators (e.g., March Industrial production) or quarterly ones (e.g. GDP estimates for Q1) did not reflect its full impact.[1] Therefore, forecasters have become avid users of high-frequency data, from old-fashioned indicators (truck traffic of electricity consump-

[1]Fig. 2 depicts the GDP at various frequencies. The monthly GDP loss during the April trough exceeds the quarterly GDP decline in Q2 as a partial recovery took place by the end of the quarter.

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tion) to modern ones (credit cards or Google Mobility Reports).[2]

Therefore, forecasters were in need of an alternative, less-constrained framework to integrate this continuous flow of economic information. Many have adopted a simple scenario-based approach, flexible enough to reflect their views. In this framework the pandemic spell is decomposed into three distinct periods:

1. The "Lockdown" started around mid-March in most Western economies and lasted for about two months. Stringent constraints on firms' activity caused a massive supply-side shock. GDP losses varied amongst countries because the intensity of the Lockdown itself varied,[3] but they often ranged between 20 and 30%.

2. A "post-Lockdown" period of 2 to 3 weeks witnessed a gradual relaxation of public-health constraints. The supply-side shock persisted but with less intensity. As economic activity gained traction, GDP surged and recovered about 50 to 60% of its initial slump in most countries.[4].

3. During the ongoing "Recovery", supply-side constraints have waned and activity has become increasingly demand-led. Policy measures aimed at boosting domestic demand, facilitating a smooth recovery of labor markets or avoiding a wave of bankruptcies determine the economic cost of the pandemic.

The Recovery period raises two important questions. First, will the pandemic have a lasting impact on the economy, with some form of hysteresis? It was initially considered that a short confinement would not impair trend GDP growth, unlike the Great Recession which depressed productivity. Yet, economists have become less sanguine about the economic recovery as the unusual violence of the shock could trigger a wave of bankruptcies and disrupt labor markets for longer than expected. Economists usually ponder whether shocks permanently affect the level of (potential) GDP and/or its growth rate (see Alichi et al. (2017)). So, is the pandemic a permanent shock on GDP levels, as depicted by the blue area in Fig. 2?

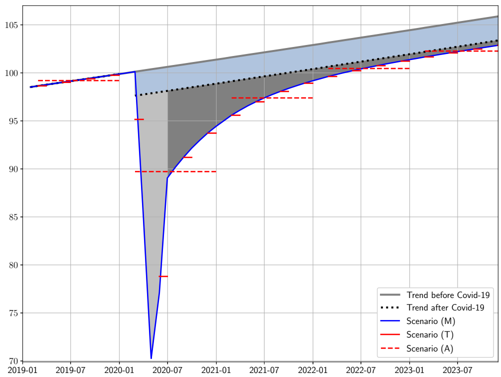
This leads to the second important question about the Recovery. After the post-Lockdown catch-up, GDP is expected to grow above trend to recoup some residual losses. Thus, at which speed will the economy revert back to its trend? International organizations have become increasingly concerned by the possibility of a protracted output gap which could last well into 2021. As an illustration, Fig. 2 assumes a weekly recovery rate of 3%, as the difference between actual GDP and its new trend (the grey dotted line) diminishes each week by 3%.

[2]See, for instance, the analysis of US consumption based on Chase credit cards in Cox (2020).

[3]See the indicators built by the Oxford's Blavatnik School of Government in Appendix A. A difficulty with these indicators is that compliance with health regulations varies among countries. Conversely, significant fractions of the population voluntarily change their behavior, sometimes anticipating the adoption of health regulations (see, Chernozhukov et al. (2020) based on Google Mobility Reports).

[4]Again, these numbers' based on partial indicators (mainly industrial production and households' consumption), are fragile until 2020 Q2 GDP numbers are released

Figure 2: A scenario for the Covid-19 crisis



Overall, these scenarios involve four parameters (1) the initial GDP loss during the Lockdown (*Shock*), (2) the extent of the post-Lockdown partial recovery (*Initial Recovery*), (3) the weekly gains during the Recovery period (*Recovery Speed*) and (4) the long-term loss as a percentage of GDP (*Long-term Loss*). These parameters can be adjusted to fit most recovery scenarios depicted in the economic press. For instance, a V-recovery corresponds to an *Initial Recovery* parameter close to 100%. They cannot describe, however, the occurrence of a second lockdown and a W-recovery.

This framework also provides a taxonomy of the various economic losses endured during the pandemic. The expected *Total Loss*, represented by all the shaded areas in Fig. 2, is the sum of the *Initial Loss* during the Lockdown and post-Lockdown, of the *Recovery Loss* during the Recovery and of the *Long-term Loss* (in blue). Note that, by construction, part of the initial slump is considered as a Long-term Loss. Overall,

$$\textit{Total Loss} = \textit{Initial Loss} + \textit{Recovery Loss} + \textit{Long-term Loss}.$$

The next Section evaluates these losses in various countries according to the CF survey.

3 The economic cost of Covid-19

This Section evaluates GDP losses for various countries, from a calibration of the above scenario with the CF survey. This calibration mobilizes GDP forecasts with different frequencies (quarterly or annual) and horizons (from the current quarter to the medium

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term).[5] Intuitively, for calibration purposes, GDP numbers for the first quarter of 2020 (2020 Q1) inform about the initial GDP drop, while 2020 Q2 GDP is driven by the hike in activity as the economy restarts. GDP growth forecasts in subsequent quarters reflect the weekly gains during the Recovery period. Finally, changes in the medium-term projections between the February and April 2020 surveys provide a gauge of the long-term losses due to the pandemic.[6]

This section focuses on the results of this calibration exercise; its technical aspects are relegated to Appendix A.

3.1 Calibration results

Table 1 provides the scenario parameters for each country. As a caveat, they are highly dependent on the assumed dates for the beginning and the end of the Lockdown, which can only be partly inferred from the data collected by the Blavatnik School of Government. Indeed, the adoption of mitigation policies was often gradual, causing geographical heterogeneity, most notably in the US. Moreover, as the Introduction mentioned, populations sometimes anticipated health regulations and altered their behavior before their introduction. Finally, Japan or Sweden's mitigation policies differed regarding their timing or intensity. Thus, the calibration also takes into account the decline in industrial production for the countries under review (see Row 2 in Table 1) to ensure that the maximum drop in GDP (*Shock*) accords with the observed decline in industrial output.[7]

Overall, the five largest European economies have performed poorly during the first phase of the pandemic. The initial GDP *Shock* is particularly high in Italy and France. Italy suffered from the worst decline because of the severity of the pandemic in its industrial North. France's estimate is in line with its statistical office's own (see INSEE (2020)). The fall was also severe in Spain, the UK and Germany but the other countries under review weathered the shock better, particularly Japan.

The *Initial Recovery* was rather homogeneous, ranging from one half to two-thirds of the initial GDP *Shock* in most countries, except in Canada. Countries that experienced

[5] Each month, Consensus Economics polls respondents from financial institutions, trade associations and research institutes about their annual GDP growth forecasts for the current year and the following one. It also publishes quarterly GDP growth forecasts, at the end of each quarter, with a seven or eight-quarter horizon. The survey also publishes long-term annual growth forecasts (up to ten years) four times a year (in February, April, August and October). As a caveat, I only had access to the hard-copy, rounded version of these quarterly and long-term forecasts. Consensus Economics also warns that quarterly-forecast respondents only form a subset of annual forecasters, but potential inconsistencies in the CF survey between annual and quarterly forecasts have not been studied systematically, to the best of my knowledge.

[6] Since the full impact of the coronavirus was arguably still underestimated in the April CF survey, its results are adjusted (see Appendix A for details).

[7] For Japan and Sweden, the Covid-driven GDP drop takes place in 2020 Q2, implicitly in April in the calibration.

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Table 1: Parameters of the pandemic shock (in %)

	USA	Canada	Japan[b]	UK	Sweden[b]	Switzerland
Shock	-16.1	-16.2	-12.4	-25.4	-15.0	-18.6
Industrial Production[a]	-16.5	-18.0	-12.4	-23.6	-15.0	n.a.
Initial Recovery (as % of *Shock*)	48.1	43.4	67.8	55.6	58.9	58.9
Recovery Speed (per week)	2.61	2.12	2.19	0.85	0.44	2.21
Long-term Loss (as % of GDP)	-3.17	-2.43	-1.63	-3.13	-1.20	-1.19
	Euro zone	**Germany**	**France**	**Italy**	**Spain**	**Netherlands**
Shock	-30.3	-25.0	-35.6	-36.0	-30.4	-17.1
Industrial Production[a]	-27.8	-29.6	-33.8	-43.4	-32.7	-7.8
Initial Recovery (as % of *Shock*)	63.9	66.5	64.2	62.0	58.2	50.4
Recovery Speed (per week)	1.09	1.27	0.92	1.45	0.93	1.93
Long-term Loss (as % of GDP)	-2.10	-2.33	-2.07	-4.14	-3.71	-1.48

The Table reads as follows. In the US, the initial GDP loss amounts to 16.1% of GDP, 48.1% of which had been recovered by May-end. Subsequently, the US economy regains 2.61% each week relative to trend. The Long-term Loss amounts to 3.17% of GDP.
(a) Variation between February and April (Source OECD).
(b) Calibration based exclusively on Industrial production.

the most precipitous drop, such as Germany, France and Italy, recovered faster while the US, Canada, Switzerland and Sweden recuperated more gradually. Japan is a fortunate outlier in that it combines a small initial *Shock* with a rapid recovery.

During the ongoing *Recovery* period, the *Recovery Speed* is expected to vary among countries. In a first group of countries, the gap to the new GDP growth trend would diminish by more than 2% per week, to be halved after 6 to 8 months. In a second group comprised of the largest euro zone economies and of the UK, the recovery would be slower to the tune of 1% per week (25% after 6 months). This tepid pace probably has multiple idiosyncratic causes, from lingering doubts about mitigation policies in some countries to the heavier weight in GDP of hard-hit sectors (e.g., Tourism, Construction, Automobile) in others.

The last parameter in Table 1 measures the expected Long-term-Losses. Changes in the medium-term projections between the February and April 2020 CF surveys provide a preliminary gauge, equal to the difference between the 2025 GDP levels expected before and after the occurrence of the pandemic. Again, there are striking disparities among countries, with three distinct groups. The group of best performers includes Switzerland, Sweden, the Netherlands and Japan with a Long-term Loss below 2% of GDP per annum. A second group, comprised of Germany, France and Canada slightly exceeds this 2% threshold. The final group (the US, the UK Spain and Italy) is the hardest-hit with losses in excess of 3% and even of 4% for Italy.

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3.2 And the winner is ...

Fig. 3 illustrates how much the expected economic toll of the pandemic varies among the countries under review. The graphs' identical scales facilitate the inter-countries comparisons of initial *Shocks* and Long-term Losses. They are obviously of different magnitudes, say in Sweden and in Italy. The graphs also validate the premises of this work, *i.e.* that the pandemic is expected to reduce permanently GDP levels in affected countries but not their growth rates, since GDP curves for the two surveys are parallel in the long run.

Figure 3: Medium-term prospects after the Covid-19 crisis

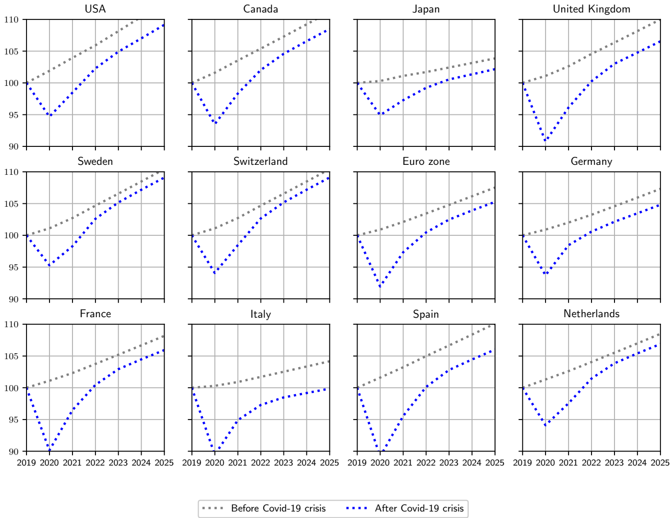

Table 2 quantifies these intuitions and allocates GDP losses according to the above taxonomy. The Total Loss, the economic cost of the pandemic between 2020 and 2025, is a measure of the area between the two GDP curves in Fig. 3. An adjusted metric is also of interest for inter-country comparisons. Indeed, the pandemic amounts in the long-run to a postponement of GDP growth by a couple of years, which is obviously more costly in fast-growing economies. The ratio of the Total Loss by trend GDP growth takes account of this effect. Intuitively, it represents the number of years of growth lost because of the pandemic. Table 2 also breaks down the Total Loss into Long-term and Cyclical Losses, the latter being the sum of the Initial Loss and the Recovery Loss.[8]

[8]Bear in mind, that the delineation between Initial and Recovery Losses depends on the calibrated scenario. Therefore, it is sensitive to discrepancies between quarterly and annual CF forecasts, which

Table 2: Medium-term impact of Covid-19 on GDP (2020-2025)
(As a % of GDP)

	USA	Canada	Japan	UK	Sweden	Switzerland
Total Loss	-25.02	-23.58	-16.79	-30.07	-15.77	-16.71
In years	-2.08	-2.12	-3.50	-2.95	-1.42	-1.51
Long-term Loss	-19.05	-14.56	-9.80	-18.80	-7.22	-7.14
Cyclical Loss	-5.97	-9.02	-6.99	-11.27	-8.55	-9.57
Initial Loss	-1.79	-2.62	-1.06	-3.19	-1.42	-2.94
Recovery Loss	-4.18	-6.40	-5.93	-8.08	-7.13	-6.63
	Euro zone	Germany	France	Italy	Spain	Netherlands
Total Loss	-22.85	-20.19	-26.02	-33.25	-35.25	-19.09
In years	-2.82	-2.59	-2.99	-7.92	-3.79	-2.19
Long-term Loss	-12.63	-13.99	-12.41	-24.81	-22.28	-8.88
Cyclical Loss	-10.22	-6.20	-13.62	-8.44	-12.97	-10.21
Initial Loss	-3.84	-2.38	-5.11	-3.86	-4.07	-2.71
Recovery Loss	-6.39	-3.81	-8.52	-4.58	-8.91	-7.50

The Table reads as follows. In the US, GDP losses amount to 25.02% of GDP between 2020 and 2025, including 19.05% due to a long-term reduction in GDP levels. This Long-term Loss represents 2.08 years of US medium term growth. The Cyclical Loss amounts to 5.97% of GDP.

On average,[9] the Total Loss reaches 23.8% of GDP, that is almost 4% p.a.. The largest fraction of this loss (60.7%) comes from Long-term Losses. Admittedly, these numbers reflect various calibration choices. For instance, the overall loss and the part attributable to Long-term losses would be lower with a shorter horizon than 2025. Also, as Fig. 2 makes clear, part of the initial slump is included in Long-Term Losses. But, qualitatively, the conclusions are inescapable: Total Losses will dwarf the economic losses resulting from two months of Lockdown.

Among the various countries, Sweden and Switzerland emerge as the expected best economic performers, by all metrics, during the pandemic, able to contain GDP losses at its initial stage and in the long run. Conversely, Spain and Italy stand at the bottom of the rankings with the two metrics. Although Spain's Total Loss is slightly higher, its higher trend growth should facilitate its recovery. Italy is in the worst position as it will have to cope with a large initial *Shock* against a backdrop of meager trend growth. Between these extremes, some economies (Japan, the Netherlands, Germany and the euro zone) are able to contain losses better than others (the US and Canada), but their pandemic burdens expressed in years are similar as the latter group benefits from higher trend growth. Finally, for France and the UK, the Total Loss is high both in absolute or in years terms.

remain reasonably low.

[9]Excluding the euro zone to avoid double counts.

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Another notable feature of Table 2 is that forecasters do not correlate Cyclical and Long-term Losses. Their low correlation (0.09) indicates that forecasters do not simply extrapolate the Total Loss from the economic loss during the first semester of 2020 (which they could assess reasonably well by the time of the July CF survey). For instance, France is predicted to bear the highest Cyclical Loss but to perform better afterwards; the opposite holds for the US. Overall, forecasters form separate judgments on the short and long-term impacts of the pandemic for each country.

Health considerations seem to play an important role when forecasters form these judgments. A regression of the Total Loss on the Death Toll[10] yields the following results:

$$\text{Total Loss} = \underset{(-5.97)}{-15.41} + \underset{(-4.04)}{-0.0247}\ \text{Death Toll.} \tag{3.1}$$

$$\text{Method: Robust LS (M setting) } R^2 = 0.49.$$

Note that Robust Least Squares limit the influence of Sweden, a clear outlier in this regression (despite similar death tolls, Sweden and Italy's economic predicted losses differ vastly). The elasticity implies that an additional 100 victims per million inhabitants increases the Total Loss by 2.47 % of GDP. For instance, given Germany's superior handling of the health crisis, its economic burden should be 9% lower than France's.

Discussion & Conclusion

Overall, the Consensus Forecast survey agrees with the IMF analysis: the Covid-19 pandemic should have a lasting negative impact and economic damages significantly exceed short-term GDP losses.[11] Another interesting finding is that the survey predicts large disparities among developed countries' economic burdens. Forecasters' expectations of Swedish good economic performance may rekindle the debate among policymakers or economists about the optimal balance between public-health and economic considerations (see, for instance, Acemoglu et al. (2020), Eichenbaum et al. (2020) or Gollier (2020)).

What could cause such a protracted reduction in economic activity? And why are some countries expected to perform better than others? CF forecasters clearly evaluate each country's public health management but other factors seem to play a role when they make their forecasts. Yet, at this stage, these factors are difficult to pin down. The current crisis might trigger changes in households' or firms' behaviors but these changes are expected to be either temporary (e.g., higher saving rates) or of limited impact on GDP (changes in work organization with increased teleworking, supply chains reorganization, etc.). Possibly, these forecasts reflect an assessment of the countries' fiscal

[10]Specifically, the Covid-19 confirmed victims per million people observed on July 13th (date of the CF survey) by the Blavatnik School of Government.

[11]Gómez-Pineda (2020) finds similar result with a slightly different approach for developed economies.

policies aimed at alleviating the pandemic crisis which differ in terms of size and by the type of instruments deployed.[12]

Whatever its origin, a long lasting shock on national income begs the question of who shoulders it. So far, most countries have postponed the adjustment of households' income, lest it aggravated the demand shock. Yet, faced with a lasting GDP shock, economic agents need to adjust. Excessive procrastination could lead to higher unemployment or public debt in the long run. As an alternative explanation for the differentiated costs of the pandemic, some countries are more successful than others at sharing a burden between households, firms or future generations.

Interestingly, equity markets participants have their own, decidedly more optimistic anticipations about this burden sharing. For instance, the *S&P* 500 earnings forecasts[13] exceed their pre-pandemic levels by the second semester of 2021, led by a bounce in revenues which surpass their 2019 reference as early as 2021 Q1. For equity markets, Covid-19 will not lead to lasting activity or profit losses...

Table 3: Medium-term forecasts for the S&P 500

		Q1	Q2	Q3	Q4	Calendar year
Earnings	2020	-15.4	-42.9	-24.3	-13.3	-23.4
	2021	11.0	64.0	32.7	23.7	30.9
	Cumul. 2020-21	-6.1	-6.3	0.5	7.3	0.2
Revenues	2020	0.1	-11.2	-5.4	-2.2	-4.8
	2021	4.1	14.9	10.7	7.8	8.6
	Cumul. 2020-21	4.2	2.0	4.7	5.4	3.4

The Table reads as follows. Earnings are expected to have dwindled by 42.9% in 2020 Q2, relative to 2019 Q2 and to rebound by 64% the following year. Hence, earnings would be 6.3% lower in 2021 Q2 than in 2019 Q2.
Source: I/B/E/S (2020)

[12] Sharma et al. (2020) suggest a theoretical link between economic policies and the shape of the recovery.

[13] From I/B/E/S, as of July, 2020.

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A Technical Appendix

This Appendix describes the underlying methodology for this note, including the data used and the calibration procedure.

A.0.1 Consensus Forecast Data

This note employs the Consensus Forecast (CF) survey, conducted monthly by Consensus Economics since October 1989. This survey polls for each country twenty to thirty respondents from financial institutions, trade associations and research institutes, about their forecasts for 10 to 15 key economic variables for the current and the following years. The note uses these GDP annual growth projections in some major industrialized economies and in the euro zone.

The CF survey provides important additional information. Every quarter, respondents forecast quarterly growth with a seven-quarter (in June and December) or eight-quarter (in March and September) horizon. Consensus Economics also publishes long-term annual growth forecasts (up to ten years) four times a year (in February, April, August and October).

In this note, the medium-term pre-pandemic outlook is based on the February forecasts included in the *Trends in Productivity and Wages* report, while the April Long-term forecasts provide a first glimpse at the forecasters' take on the impact of the pandemic.

However, annual GDP forecasts for 2020 and 2021 were substantially revised in May and in subsequent surveys, with a deteriorated outlook for 2020 GDP growth partly compensated by higher growth in 2021. Therefore, medium-term forecasts were adjusted as follows. In 2020 and 2021, the GDP growth rates from the last available survey (July) are employed. GDP growth is adjusted upward for 2022 and 2023 so that 2023 GDP levels are identical to those obtained with the April survey.[14]

A.0.2 Dates of the Lockdown

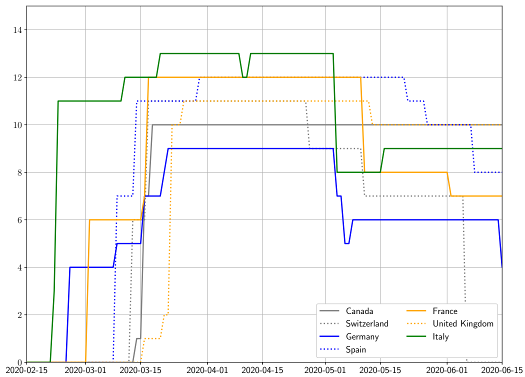
The choice of the beginning and the end of the Lockdown period is partly subjective. This note relies on the dataset collated by Oxford's Blavatnik School of Government (see Hale et al. (2020)), frequently used by economic newspapers and for research. It contains 17 daily indicators for 180 countries which describe public-health measures, in particular in terms of containment and closure, economic and public-health regulations. These indicators are scaled to reflect their stringency.

This paper uses a sub-group of indicators, selected because the underlying public-health

[14] With 70% of the adjustment in 2022 and 30% in 2023. Note that with less-than-full compensation, Long-term Losses would be even higher.

measures are likely to have a significant economic impact (schools closing, workplace closing, public transportation closing and stay-at-home orders). Fig. 4 depicts for a subset of countries the overall index, calculated by summing the indicators in the sub-group.

Figure 4: the Oxford Blavatnik Index



For reasons discussed in the main text, this index does not always reflect the effective impact of mitigation policies. Thus, the Lockdown dates, provided in Table 4, are adjusted so that the initial *Shock* is in line with the variation of industrial production between February and April.

Table 4: Lockdown dates

	USA	Canada	Japan[a]	UK	Sweden[a]	Switzerland
Start date	21	18	25	23	30	17
End date	25	25	1	25	1	1

	Euro zone	Germany	France	Italy	Spain	Netherlands
Start date	20	23	17	18	14	20
End date	11	4	11	11	27	11

(a) The Lockdown dates are not used for the *Shock* calibration.

A.0.3 Calibration procedure

Let us denote by gdp_Y, the annual GDP index for Year Y, by gdp_{Y,m_i} and gdp_{Y,q_j} the monthly and quarterly annualized GDP indices, respectively for month i and quarter j, and by g_{Y,q_j} the index's quarterly growth rate. A superscript indicates the time of the forecast. For instance, g^{Feb}_{Y,q_i} is the quarterly growth forecast made in February before the pandemic starts.

The *Long-term Loss* parameter is calibrated as the difference in expected GDP in 2025 between the two scenarios, that is:

$$\textit{Long-term Loss} \;=\; \frac{GDP^{Apr}_{2025} - GDP^{Feb}_{2025}}{GDP^{Feb}_{2025}}$$

To calibrate the initial shock on GDP (*Shock*), it is assumed that the monthly GDP indices are such that

- $gdp_{2019,m_{12}} = 100$ and $gdp_{2019,q_4} \approx 100 * (1 - g_{2019,q_4}/2)$;
- GDP growth is in line with pre-pandemic expectations until the start of the Lock-down on March, d_1.

Hence,

- $gdp_{2020,m_{01}} = 100\ (1 + gdp^{Feb}_{2020,q_1})^{1/3}$,
- $gdp_{2020,m_{02}} = 100\ (1 + gdp^{Feb}_{2020,q_1})^{2/3}$,
- $gdp_{2020,m_{03}} = 100\ (1 + gdp^{Feb}_{2020,q_1})^{(60\,+\,d_1)/91} * (\frac{d_1}{31} + Shock\frac{31 - d_1}{31})$.

These equalities provide a linear relation between *Shock* and the quarterly GDP growth rate in 2020 Q1, g^{Apr}_{2020,q_1} from which *Shock* is inferred. Note that the earlier the shock in March, the more accurate the calibration.

Using again monthly GDP indices, the *Initial Recovery* and *Recovery Speed* are jointly determined as follows. In April and early May, the monthly GDP index remains at the depressed level reached by March-end. Then, it recovers by an amount equal to *Initial Recovery* until the end of May. From June onward, the index growth depends on the difference between its level and its new trend $trend_{m_i}$, (that is the previous trend reduced by *Long-term Loss*). Hence

$$gdp_{2020,m_{i+1}} - trend_{m_{i+1}} \;=\; (1 - RecoverySpeed)^4\ \left(gdp_{2020,m_i} - trend_{m_i}\right)$$

(Bear in mind that *Recovery Speed* is measured on a weekly basis.) From this relation, one can infer quarterly GDPs from the two parameters. Conversely, the value of the parameters can be obtained, by a fixed-point algorithm, to match the values of the forecasts for g_{2020,q_2} and g_{2021,q_1}.

Finally, for Japan and Sweden, the *Shock* parameter is directly inferred from the industrial production. The same algorithm is used but assumes that GDP is equal to its post-*Shock* level on the first day of April.

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