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THE ECONOMIC LINKAGES OF COVID-19 ACROSS SECTORS AND REGIONS IN THE UK

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The Economic Linkages of Covid-19 Across Sectors and Regions in the UK*

Fidel Pérez-Sebastián† Rafael Serrano-Quintero‡

September 2023

Abstract

This paper builds a spatial model of trade with supply-chain links to try to understand the effect of economic links and policies on the spread of the Covid-19 pandemic during the first wave across NUTS2 UK regions. We find that the fight to reduce infection rates was more successful in the UK than in the European Union. Our results imply that without the policy reaction in Europe, the number of deaths during the first wave of the pandemic would have been about 4,400,000 larger in the European Union and about 1,217,000 higher in the UK, and that these benefits vary greatly across UK regions. Comparing the effects of the policies implemented in the EU27 and in the UK, we estimate that, in the absence of European-Union's anti-Covid-19 measures, the number of deaths in the UK would have been an 80% larger; and that UK anti-Covid-19 measures saved 50,000 lives in the European Union and 1,200,000 lives in the UK.

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1 Introduction

The recent COVID-19 pandemic has ended 4.55 million lives (as of October 1^{st}, 2021), forced quarantines all over the world, stopped global value chains for a significant amount of time, and created one of the largest global recessions in recent years. However, as with the spread of other infectious diseases, its impact in terms of lives and economic activity has varied greatly across regions and industries (see, e.g., Villani et al. (2020) and de Vet et al. (2021)). In this paper, we build on the idea that diffusion of infectious diseases depend on human interactions (e.g.,

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see Fogli and Veldkamp (2021)), and in particular, on how dense is the economic network of a given area. We consider endogenously determined economic interactions and analyze the effect of the policies adopted to fight the first wave of the pandemic across different regions in the UK. More specifically, the paper asks the following questions. What is the contribution of economic linkages to the expansion of the disease? How many lives have the polices implemented saved?

The model we develop embeds an spatial economic model in the spirit of Allen and Arkolakis (2014); Caliendo and Parro (2014) and Caliendo et al. (2017) into the canonical Susceptible, Infected, Recovered (SIR) model by Kermack et al. (1927). The purpose of the proposed framework is to analyze the two way causation between the spatial dynamics of an epidemic and the spatial distribution of economic activity. More specifically, the setup incorporates Ricardian trade *á la* Eaton and Kortum (2002), and extends the SIR model in two ways. First, similar to Fernández-Villaverde and Jones (2020), we consider five population groups composed of susceptible, vaccinated, infected, resolving, and recovered individuals, and also account for deaths. Second, we allow for spatial connections that are endogenously determined by the structure of our economic geography model. The assumption is that when regions trade, people enter in contact with one another so they put themselves at risk of getting infected or that the virus is itself transported through the imported goods. As a result of the economic geography model, denser regions will experience more rapid increase in infections for two reasons. First, within the region, there are more interactions across individuals and thus, a higher probability of transmission. Second, the larger a region is, the more it will trade with other regions, and thus, the higher the probability of transmitting the disease across regions.

In our framework, the economy is composed of a set of locations that produce goods in different sectors. Each sector produces three goods: a final product, an intermediate good, and a composite intermediate or material. The first two can be traded but trade is costly. The third one is only sold domestically within the region. In addition, following Caliendo and Parro (2014), whereas the domestic movement of materials is inter-industry, cross-regional trade of intermediate goods is purely intra-industry.[1] This feature captures that the latter type of trade represents the largest component of the trade flows of intermediates. For example, World Bank (2009) finds that, from 1962 to 2006, worldwide intra-industry trade in intermediate goods increased approximately from 30% to 60% of total trade. This share equals 42 percent in our European Union 28-country group (EU28) dataset for the year 2013. What is most important is that these inter- and intra-industry links across sectors mean that policies and changes that affect a given industry can potentially affect all other sectors and regions. Our main contribution is to assess

[1] Compared to the sectoral structure presented by Caliendo and Parro (2014), the main difference with ours is that we consider that final consumption products can cross regional borders. The reason is that some of them, like tourism, can be important for the propagation of the virus and are tradable.

how the heterogeneity in production structures and regional connections affect the spread of the disease and its economic impact.

The model proceeds in two phases. For a given the population composition, the first phase obtains the distribution of economic activity and bilateral trade shares. In the second phase, we take as given the bilateral trade shares and the spatial distribution of economic activity along with the disease ecology to determine how the population composition changes from one week to the next. This creates a loop in which disease dynamics and economic activity affect each other. In particular, disease prevalence can reduce the labor force in a region through either mortality, morbidity or policy actions. These shocks affect the level of economic activity and reduce international trade. The modification of the trade patterns, in turn, has an impact on the spread of the disease by decreasing the amount of infection *"exported"* to other regions. These general equilibrium forces resemble a behavioral response in which agents protect themselves from the infection.

The explicit modelling of the geography is important to understand the disease dynamics.[2] In general, those regions that are more isolated will receive and transmit less the infection. As an example, take the evolution of the pandemic in Spain versus Italy and the UK. The spread of the infection in Spain was faster in Madrid (a region in the center of the country) and then expanded throughout the nation. In Italy, the infection started in the north and then moved slowly towards the south. In the UK, in turn, the disease was more concentrated in the south but, at the same time, more widespread than in other parts of Europe. Our model addresses these singularities through the explicit modelling of the geography of trade in Europe.

We calibrate the model to match the distribution of workers and wages across 230 regions from 28 countries in Europe for 10 sectors of production comprising the whole economy and use our framework to assess through a set of counterfactuals, how policies adopted during the coronavirus pandemic, which include social distancing and regional lockdowns, have affected the impact of the disease. We focus on the first wave that goes from February 25^{th} to July 15^{th}, 2020.

We find that, even though the incidence of the disease was larger in the UK than in the European Union, the fight to reduce the infection rates was more successful in the former economy than in the latter. Our results also imply that without the policy reaction in Europe, the number of deaths during the first wave of the pandemic would have been about 4,400,000 larger in the European Union and about 1,217,000 higher in the UK, and that these benefits greatly vary across UK regions. Comparing the effects of the policies implemented in the EU27 and in the

[2] Wilson (2010) surveys the literature on the links between geography and infectious diseases and notes that socioeconomic conditions, public health infrastructure, urban versus rural environments, density and mobility of the population are important factors explaining the types and abundance.

UK, we estimate that, in the absence of European-Union's anti-Covid-19 measures, the number of deaths in the UK would have been an 80% larger, which would have implied 34 additional deaths per 100,000 inhabitants. Finally, UK anti-Covid-19 measures saved 50,620 lives in the European Union and about 1,200,000 lives in the UK.

The paper proceeds as follows. Section 2 describes the related literature. Section 3 introduces the model. The calibration of its exogenous variables and parameters is discussed in section 4. Section 5 presents the results. Section 6 concludes.

2 Related Literature

Our paper contributes to a large and growing literature on the economic interactions and infectious diseases. We motivate our modelling strategy based on the empirical evidence supporting the link between economic interactions and infectious diseases. Several early examples showed the importance of diseases in developing countries. Chakraborty et al. (2010) introduce rational disease behavior in a general equilibrium framework focused on the effects of the burden of malaria and the HIV infection on economic development. They show that these diseases can be a source of economic growth traps. Oster (2012), it turn, shows in the context of Africa, that engaging in exports leads to a large and significant increase in new HIV infections mainly due to the movement of truckers.

The connection between trade and infectious-disease transmission is not only prevalent in developing countries. Adda (2016) provides evidence based on microdata that the expansion of transportation networks and interregional trade had a significant impact on virus spreading in France. Focusing on European pandemics going back to the 14^{th} century, Jorda et al. (2020) find important long-run economic consequences even after 40 years. In the context of COVID-19 in the United States, Desmet and Wacziarg (2021) show that population density of a county is persistently correlated with its COVID-19 severity. We contribute to this strand of the literature by constructing and calibrating a model for a set of European regions at different stages of development and assessing the importance of trade on the spread of the disease.

We are not the first in introducing spatial connections in epidemiological models. Lloyd and May (1996) and Keeling (1999) are early examples of spatial models of epidemics. Paeng and Lee (2017) extend the canonical SIR model by including spatial infections assuming that the infection can be spread in a given radius. In the epidemiological literature, the connection between trade and the spread of infectious diseases is also known, Mayer (2000) notes that vectors of transmission of dengue fever or cholera were introduced in the U.S. through imported tires and through dumping bilge water into the ocean. We depart from this literature by endogenizing the spatial connections within a quantitative economic geography model, instead of assuming a given radius of infection or stochastic encounters.

More closely related to our context, Antràs et al. (2020) build a two-country framework of human interactions in which they combine a gravity equation structure and an epidemiological model of disease evolution. In their model, the disease spreads as agents travel from one country to another. We depart from them by building a multi-country and multi-sector setup with an input-output structure rich enough to capture the transmission of the disease through bilateral trade across all the network nodes. The inclusion of different sectors can also allow us to consider a wider array of policies, like selected closures.

We use our model to address the effect of region-specific lockdown policies during the first wave of the pandemic and the trade-off between the spread of the disease and potential losses from not engaging in trade. Recent papers study optimal lockdown policies focusing on different group populations (Acemoglu et al., 2020), the intensity and duration of the policy (Alvarez et al., 2020), and the distributional consequences (Glover et al., 2020). More closely to our context, Fajgelbaum et al. (2020) find that regional-specific lockdowns result in better outcomes than uniform lockdowns. We depart from them by analyzing the policy effects at a higher regional level, but our result go in line with theirs. We also depart from them in that we consider deaths as a crucial vector affecting the labor supply.

Our article also talks to another branch of recent papers focused on consumer behavior and output responses when faced with an infectious disease (Eichenbaum et al., 2020; Guerrieri et al., 2020; Krueger et al., 2020). Crucially, we depart from them by looking at the differential effects of having an open economy, multiple regions, and a rich input-output structure. Çakmaklı et al. (2021) study how demand and supply shocks affect global vaccinations and how vaccinations of other countries can potentially benefit home countries. They do not include, however, endogenous links for the spread of the infection. We also extend the methodology by Fernández-Villaverde and Jones (2020) to recover infection rates based on future deaths and use it to calibrate our model with endogenous links in the disease.

3 The model

We assume the economy is composed of a set of G geographical locations or regions that belong to different countries and J sectors or industries. Regions are denoted by g, i and h and sectors by j and k. In each industry, there is production of a composite intermediate or material, an array of different varieties of intermediate goods, and a set of different types of final consumption goods. Households provide labor to the production process. Labor is mobile across sectors and immobile across locations. All markets are perfectly competitive.

We abstract from the movement of workers across locations, because this aspect does not seem to have played a significant role during the pandemic due, among other things, to the mobility restrictions imposed. In the model, the effect of the movement of people to the spread of the virus will be captured by the level of activity in sectors related to transportation and tourism.

The model offers a rich supply chain structure. Local materials from different sectors are employed along with the labor input to produce intermediate goods. In the next stage, intermediate goods produced by the same industry possibly in different locations are combined to generate final consumption products and a composite intermediate or material. These connections among the different stages of the production chain can provide amplification effects of trade disruptions.

We suppose that the intermediate goods and final products can be tradable or not, whereas materials are not tradable. We consider that final consumption products can cross regional borders, because some of them, like tourism, can be important for the propagation of the virus and are tradable. Trade in intermediate goods is intra-industry, which represents the largest component of the world trade flows of intermediates.

Let us now move to describing the model demographics. For simplicity, we omit time subscripts. The size of the population in region g equals N_g. This population is composed of five groups: susceptible vaccinated and susceptible non-vaccinated people—denoted by V_g and S_g, respectively—who are not infected but can develop the disease; infected individuals, I_g; resolving cases R_g who can pass away with probability δ or recover with probability $(1-\delta)$;[3] and recovered C_g, who can potentially get reinfected. Hence, it must be satisfied that

$$N_g = S_g + V_g + I_g + R_g + C_g. \tag{1}$$

We will consider the possibility that recovered and vaccinated individuals may rejoin the susceptible non-vaccinated population once the partial immunity acquired by being exposed to the virus or the vaccine is lost.

Only a fraction l_{gH} from each group H can supply labor services. This fraction l_{gH} will be taken as exogenous, given by morbidity and policy considerations. Then, the available labor force L_g equals:

$$L_g = l_{gS}S_g + l_{gV}V_g + l_{gI}I_g + l_{gR}R_g + l_{gC}C_g. \tag{2}$$

With these ingredients, the model can be numerically solved through a loop that consists of two phases. In the first phase, given the population composition, we can obtain the spatial distribution of economic activity. The second phase takes as given the spatial distribution delivered by the first phase, along with the disease ecology to determine how the population composition

[3]Resolving cases are infected individuals that cannot infect other people. Fernández-Villaverde and Jones (2020) suggest that distinguishing between infection and recovery periods matters for the model to fit the data well with biologically sensible parameters.

changes from one day to the next. We consider that the infection can spread within and across locations because of people contact. Finally, the new population composition feeds again the first phase, and this loop continues until predictions for the desired number of weeks are generated.

3.1 Phase 1: Economic Allocations Across Space

The first phase of the model determines the underlying economic geography through which the virus and the economic consequences of policies will potentially spread.

3.1.1 Households

Welfare-maximizing consumers in each location have identical preferences given by:[4]

$$W_g = \prod_{j=1}^{J} \left(c_g^j\right)^{\alpha_g^j}; \tag{3}$$

where

$$c_g^j = \left[\int_0^1 c_g^j(\Omega^j)^{1-1/\varsigma^j} d\Omega^j\right]^{\varsigma^j/(\varsigma^j-1)}; \tag{4}$$

the parameter α_g^j represents the share of sector-j products in total consumption expenditure in location g, that is, $\sum_{j=1}^{J} \alpha_g^j = 1$; the variable $c_g^j(\Omega^j)$ denotes the units consumed in location g of variety Ω^j from sector-j (Ω^j is one among a mass of size *one* of different varieties); and the parameter ς^j gives the elasticity of substitution between different varieties of sector-j consumption products.

In each location, the population size N_g is divided between workers L_g and non-workers $N_g - L_g$. Each of the two consumer types has, in principle, a distinct budget constraint, because income may differ depending on whether they work or not. However, we assume that workers pay lump-sum unemployment insurance (t_g) at the location were they provide labor services, and these taxes are fully redistributed as unemployment benefits (s_g) to the non-working individuals at the local level, that is, $t_g L_g = s_g(N_g - L_g)$. Furthermore, this redistribution is such that their incomes are equalized, $w_g - t_g = s_g$; where w_g is the wage rate. Which implies that $t_g = (N_g - L_g)w_g/N_g$ and then $w_g - t_g = L_g w_g/N_g$. That is, if there are more individuals unemployed, income per capita falls; and the opposite occurs if more people work. We also consider that consumers may pay lump-sum taxes τ_g that are directed to provide subsidies to firms. Therefore, letting l_g be the fraction of workers in region g (i.e., $l_g = L_g/N_g$), the budget constraint—which is the same for all consumers—can be written as:

[4]The assumption of a unitary elasticity of substitution in consumption might seem restrictive at first. However, it is worth pointing out that consumption in our framework denotes consumption of gross output, that is, final consumption expenditure. Herrendorf et al. (2013) estimate an elasticity of substitution in the range of $0.85-0.89$ but also show that an elasticity of 1 can fit aggregate consumption shares as good as a CES. As the number of sector increases, our assumption of a unitary elasticity becomes more credible.

$$l_g w_g + \frac{F_g + \tilde{D}_g}{N_g} - \tau_g = \sum_{j=1}^{J} \int_0^1 P_g^j(\Omega^j) c_g^j(\Omega^j)\ d\Omega^j; \tag{5a}$$

where $P_g^j(\Omega^j)$ is the price of variety Ω^j from sector-j consumed in g. The government of region g can also collect revenues from tariffs (F_g) that are redistributed to the whole local population. The term $\tilde{D}_g$ represents the regional trade deficit. Financing a trade deficit requires the inflow of resources from other locations, and this is why $\tilde{D}_g$ appears in the consumer's budget constrain. Notice as well that this variable can be used in the experiments as a fiscal policy tool.

Given these preferences, the optimality conditions imply that the share of variety Ω^j in consumption expenditure on the goods produced by industry j is a function of relative prices and the elasticity of substitution. In particular,

$$\frac{P_g^j(\Omega^j) c_g^j(\Omega^j)}{P_g^j c_g^j} = \left[\frac{P_g^j(\Omega^j)}{P_g^j}\right]^{1-\varsigma^j}; \tag{6}$$

where P_g^j represents the ideal price index of the sector-j final products, which equals

$$P_g^j = \left[\int_0^1 P_g^j(\Omega^j)^{1-\varsigma^j} d\Omega^j\right]^{1/(1-\varsigma^j)}. \tag{7}$$

They also confirm that consumption expenditure on sector j products in a location g is a constant fraction of total income given by α_g^j.

Taking into account that budget constraint (5a) says that income is fully spent in buying consumption goods, we can write welfare, equation (3), using an indirect utility function approach as:

$$W_g = \frac{y_g}{P_g}; \tag{8}$$

where y_g is income per capita in region g, which equals

$$y_g = l_g w_g + \frac{F_g + \tilde{D}_g}{N_g} - \tau_g; \tag{9}$$

and P_g provides the ideal consumption price index that households face in location g,

$$P_g = \prod_{j=1}^{J} \left(\frac{P_g^j}{\alpha_g^j}\right)^{\alpha_g^j}. \tag{10}$$

Note that welfare depends on the fraction of workers l_g and on the per-capita trade deficit and tariff revenue. Thus, shocks to a sector affect welfare through the trade deficit, the tariff revenues and the price index. Furthermore, constraining the share of working individuals in a region has *ceteris paribus* first order effects on welfare.[5]

[5] In order to derive (8), notice that the indirect utiity functions for working (W_g^L) and non-working (W_g^{NL})

3.1.2 Firms

In each location g, a firm that operates in sector j produces either an intermediate-good variety ($q_g^j(\omega^j)$, $\omega^j \in (0,1)$), a final-product variety ($Q_g^j(\Omega^j)$, $\Omega^j \in (0,1)$), or a composite intermediate or material ($Q_g^{\mathcal{M}j}$). The production of intermediate goods uses labor and materials from other industries, whereas the production process of final goods and materials demand intra-industry intermediates. Intermediate-good manufacturers and final-good and material producers in sector j may benefit from subsidization rates s_g^j and $\mathfrak{s}_g^j$, respectively, which reduce the costs of the different production inputs in the same proportion. All markets are perfectly competitive and firms maximize profits. We next describe in more detail each of the different stages of the production chain.

3.1.3 Intermediate goods

A firm in sector j produces a variety ω^j of intermediate goods using labor ($L_g^j(\omega^j)$) and composite intermediates from every other sector k ($m_g^{kj}(\omega^j)$) according to the production function:

$$q_g^j(\omega^j) = a_g^j \; z_g^j(\omega^j) L_g^j(\omega^j)^{\gamma_g^j} \prod_{k=1}^{J} m_g^{kj}(\omega^j)^{\gamma_g^{kj}}; \tag{11}$$

where a_g^j is sector j's fundamental productivity in intermediate-goods manufacturing by region g; $z_g^j(\omega^j)$ is a random sector-variety-specific productivity shock; and γ_g^j denotes the share of value added on gross output. The term affected by the product operator provides the use of materials from all other sectors, with γ_g^{kj} representing the expenditure share of the material from sector k employed in the input composite of the intermediate good produced by industry j. We assume that $\sum_{k=1}^{J} \gamma_m^{kj} = 1 - \gamma_g^j$. Production functions, then, exhibit constant returns to scale.

Because markets are perfectly competitive and firms are profit maximizers, intermediate-good prices must equal marginal costs, $b_g^j/[a_g^j \; z_g^j(\omega^j)]$; where b_g^j gives the cost of a unitary input bundle once subsidies are taken into account. The cost b_g^j is common to all varieties and given by

$$b_g^j = (1 - s_g^j)\Upsilon_g^j w_g^{\gamma_g^j} \prod_{k=1}^{J} \left(P_g^{\mathcal{M}k}\right)^{\gamma_g^{kj}}; \tag{12}$$

individuals are, respectively,

$$W_g^L = \frac{1}{P_g}\left(w_g - t_g + \frac{F_g + \tilde{D}_g}{N_g} - \tau_g\right) \text{ and } W_g^{NL} = \frac{1}{P_g}\left(s_m + \frac{F_g + \tilde{D}_g}{N_g} - \tau_g\right).$$

Defining $N_g W_g = L_g W_g^L + (N_g - L_g) W_g^{NL}$ as total welfare in a location, W_g is given by

$$W_g = \frac{L_g}{N_g} W_g^L + \left(1 - \frac{L_g}{N_g}\right) W_g^{NL},$$

which, substituting each of the indirect utility functions, and recalling that $s_m = w_g - t_g = w_g L_g / N_g$ and that l_g represents the fraction of working individuals in a location g, we get equation (8) where the constant Υ_g^j equals

$$\Upsilon_g^j = \left(\frac{1}{\gamma_g^j}\right)^{\gamma_g^j} \prod_{k=1}^{J} \left(\gamma_g^{kj}\right)^{-\gamma_g^{kj}} ;$$

$P_g^{\mathcal{M}k}$ is the price of the composite intermediate produced by sector k in region g; and w_g denotes the wage rate in location g. Equation (12) says that the subsidy will translate into lower prices because it complements market revenues at paying for the inputs. Notice that the term $1 - s_g^j$ can be written as a common factor because of constant returns to scale and because production subsidies reduce all input costs by the same proportion.

3.1.4 Final products

In each sector-region (j, g) pair, a set of final goods indexed by Ω^j are produced under perfect competition using intermediate goods from the same sector following a Dixit-Stiglitz aggregator with a constant elasticity of substitution $\sigma^j > 1$:

$$Q_g^j(\Omega^j) = A_g^j Z_g^j(\Omega^j) \left[\int_0^1 r_g^j \left(\omega^j\right)^{1-1/\sigma^j} d\omega^j\right]^{\frac{\sigma^j}{\sigma^j - 1}} ; \tag{13}$$

where A_g^j is the sector-region fundamental productivity in final-goods production; $r_g^j\left(\omega^j\right)$ represents the demand in region g for intermediate good ω^j from the lowest-cost supplier, which can belong to any of the regions.

Profit maximization implies the following demand function for each or the varieties:

$$r_g^j\left(\omega^j\right) = \left[\frac{(1-\mathfrak{s}_g^j)\, p_g^j\left(\omega^j\right)}{B_g^j}\right]^{-\sigma^j} \frac{Q_g^j(\Omega^j)}{A_g^j Z_g^j(\Omega^j)}; \tag{14}$$

where $p_g^j\left(\omega^j\right)$ is the price of intermediate good ω^j in location g; and B_g^j gives the cost of the input bundle with subsidies already embedded as

$$B_g^j = (1-\mathfrak{s}_g^j) \left[\int_0^1 p_g^j\left(\omega^j\right)^{1-\sigma^j} d\omega^j\right]^{\frac{1}{1-\sigma^j}} . \tag{15}$$

Equation (14) implies that the demand of intermediate ω^j per unit of final output depends on the ω^j's price relative to the price of the other varieties of intermediates. Consequently, as a response to the subsidy, the amount for intermediate products demanded can increase, not because of a change in the price that firms perceived $((1-\mathfrak{s}_g^j)\, p_g^j\left(\omega^j\right))$, but because of the decrease in the price of the final output (given by the marginal cost), which can cause an increase in $Q_g^j(\Omega^j)$.

3.1.5 Composite intermediate goods

Production of materials in sector j uses a very similar technology to the one of final goods. In particular,

$$Q_g^{\mathcal{M}j} = A_g^j \left[\int_0^1 r_g^j(\omega^j)^{1-1/\sigma^j} d\omega^j\right]^{\frac{\sigma^j}{\sigma^j - 1}} . \tag{16}$$

That is, it also combines varieties of intermediate goods coming from the same sector. The difference with equation (13) is that productivity in the case of the production of the composite intermediate is fully deterministic. Clearly, the demand for intermediate inputs will be very similar to the one delivered by final goods; in particular,

$$r_g^j\left(\omega^j\right) = \left[\frac{\left(1-\mathfrak{s}_g^j\right) p_g^j\left(\omega^j\right)}{B_g^j}\right]^{-\sigma^j} \frac{Q_g^{\mathcal{M}j}}{A_g^j}; \tag{17}$$

Because composite intermediate goods do not engage in inter-regional trade, the price paid for them by intermediate-goods manufacturers is directly given by the marginal cost of production in the same location. This implies that

$$P_g^{\mathcal{M}j} = \frac{B_g^j}{A_g^j}. \tag{18}$$

3.1.6 Inter-regional trade and destination prices

Intermediate goods and final products can travel across locations. Inter-regional trade is costly. Trade costs combine tariffs and iceberg transportations costs. We consider that tariff may be different for intermediate and final goods. More specifically, a sector-j intermediate imported by region g from location i involves a trade cost equal to

$$\kappa_{gi}^j = \left(1+\tau_{gi}^j\right) d_{gi}^j; \tag{19}$$

where τ_{gi}^j is the imposed ad-valorem tariff on intermediate goods from sector j. The transportation cost d_{gi}^j implies that the arrival of one unit of an intermediate product to g coming from i requires sending d_{gi}^j units produced of that product. For the case of final goods, trade costs equal

$$K_{gi}^j = \left(1+T_{gi}^j\right) \mathfrak{d}_{gi}^j. \tag{20}$$

Now T_{gi}^j represents the tariff on final goods from industry j, and $\mathfrak{d}_{gi}^j$ the iceberg costs related to trade in final goods. Because we will use changes in iceberg costs as proxies to study the effect of supply-chain disruptions, it is only assumed that $d_{gi}^j, \mathfrak{d}_{gi}^j \geq 1$ for all g and i. For the same reason, the usual triangular inequality $\kappa_{gi}^j \leq \kappa_{hi}^j \kappa_{gh}^j$ and $K_{gi}^j \leq K_{hi}^j K_{gh}^j$ may not hold for all g, i and h.

Taking into account these trade costs, the prices at destination of the traded products from the lowest-cost supplier are the following:

$$p_g^j(\omega^j) = \min_{i\in[1,G]} \left\{\frac{b_i^j \kappa_{gi}^j}{a_g^j z_g^j(\omega^j)}\right\} \tag{21}$$

and

$$P_g^j(\Omega^j) = \min_{i\in[1,G]} \left\{\frac{B_i^j K_{gi}^j}{A_g^j Z_g^j(\Omega^j)}\right\}. \tag{22}$$

Equations (21) and (22) say that the price at destination will be given by the minimum across locations of the product between the marginal cost and the trade cost. A more expensive input bundle or higher trade costs will push the price up, whereas a larger productivity will push it down.

Following Eaton and Kortum (2002), trade in the model obeys a Ricardian motive generated by a random allocation of productivities across sectors and regions. In particular, the realizations of the productivity variables z_g^j and Z_g^j for varieties ω^j and Ω^j follow Fréchet distributions with location parameter equal to *one* and sector-specific shape parameters θ^j and Θ^j, respectively. A smaller value of the shape parameter implies a larger dispersion of the distribution. We suppose that the random productivity variables are independently distributed across goods, industries and regions, and that $1+\theta^j > \sigma^j$ and $1+\Theta^j > \varsigma^j$. Results in Caliendo and Parro (2015) imply that, with these assumptions on the distribution of efficiencies, the distribution of prices allow rewriting equations (15) and (7) as

$$B_g^j = (1-\mathfrak{s}_g^j)\ \Gamma\left(1+\frac{1-\sigma^j}{\theta^j}\right)^{1/(1-\sigma^j)}\left[\sum_{i=1}^{G}\left(\frac{b_i^j\kappa_{gi}^j}{a_i^j}\right)^{-\theta^j}\right]^{-1/\theta^j}, \tag{23}$$

$$P_g^j = \Gamma\left(1+\frac{1-\varsigma^j}{\Theta^j}\right)^{1/(1-\varsigma^j)}\left[\sum_{i=1}^{G}\left(\frac{B_i^jK_{gi}^j}{A_i^j}\right)^{-\Theta^j}\right]^{-1/\Theta^j}; \tag{24}$$

where $\Gamma(\cdot)$ is the gamma function.

In the case that a sector is not tradable, which implies that all the varieties of intermediate goods and consumption products from that sector are bought from domestic producers, Caliendo and Parro (2015) also show that the relevant price indices amount to imposing that $\kappa_{gi}^j = K_{gi}^j = \infty$ for all $i \neq g$ in equations (23) and (24). Then, we end up with $B_g^j = (1-\mathfrak{s}_g^j)\ \Gamma(1+(1-\sigma^j)/\theta^j)^{1/(1-\sigma^j)}b_g^j/a_g^j$ and $P_g^j = \Gamma(1+(1-\varsigma^j)/\Theta^j)^{1/(1-\varsigma^j)}B_g^j/A_g^j$.

3.1.7 Expenditure Shares

Let x_g^j and X_g^j be region g's total expenditures on intermediate goods and final products from sector j, respectively. They are obtained at destination prices, and therefore, include tariff payments. Define x_{gi}^j and X_{gi}^j as the expenditures in location g on sector-j intermediate goods and sector-j final products, respectively, imported by location g from location i. Finally, let π_{gi}^j and Π_{gi}^j be region g's total expenditure shares of intermediate goods and final products from sector j exported by location i to location g, respectively; that is, $\pi_{gi}^j = x_{gi}^j/x_g^j$ and $\Pi_{gi}^j = X_{gi}^j/X_g^j$. Caliendo and Parro (2015) show that

$$\pi_{gi}^j = \frac{\left(b_i^j\kappa_{gi}^j/a_i^j\right)^{-\theta^j}}{\sum_{h=1}^{G}\left(b_h^j\kappa_{gh}^j/a_h^j\right)^{-\theta^j}}, \tag{25}$$

$$\Pi_{gi}^{j} = \frac{\left(B_i^j K_{gi}^j / A_i^j\right)^{-\Theta^j}}{\sum_{h=1}^{G}\left(B_h^j K_{gh}^j / A_h^j\right)^{-\Theta^j}}. \tag{26}$$

Bilateral trade shares contain important information. First, they are declining on transport costs and increasing in the productivity of the producer (since this productivity reduces the marginal cost directly). Second, they include information on the input-output structure of the whole economy through the prices paid for intermediate inputs. Furthermore, this input-output structure is also affected by the economic geography, since intermediate inputs can be imported from abroad. In terms of the effects of policies regarding the control of COVID-19, this gravity equation is potentially informative for several reasons. It can potentially capture the fact that some sectors might be more affected by social distancing policies, since sectors can differ in their labor input intensities. Dingel and Neiman (2020) estimate that, in the U.S., the share of jobs that can be done from home significantly varies across cities and industries and also show that this share is decreasing in the level of development of the countries. Our model could plausibly capture this. Our model could also show the effects of how shutting down a certain sector or region, would affect the rest of sectors and locations through the input-output structure. Furthermore, in the second phase of the model, infections can be spread through economic linkages, since some sectors are more interconnected than others, those regions that are more intensive in certain inputs can show significantly faster infection rates.

3.1.8 Market clearing and government and regional deficits

Local labor markets require that the sum of labor employed in the different industries equals the total amount of labor available in the region. Formally,

$$\sum_{j=1}^{J} L_g^j = L_g \tag{27}$$

Furthermore, because in equilibrium labor costs must equal a constant fraction γ_g^j of the value of the intermediate-goods production, the following condition must hold:

$$w_g L_g = \sum_{j=1}^{J} \frac{\gamma_g^j}{1 - s_g^j} \sum_{i=1}^{G} \frac{x_i^j \pi_{ig}^j}{1 + \tau_{ig}^j}. \tag{28}$$

Notice that the right hand side (RHS) of equation (28) adds the expenditures across sectors and regions on intermediate goods manufactured in location g that go to pay the labor input. It also implies that payments to labor are in part satisfied using the subsidies, in an amount equivalent to a fraction $\gamma_g^j s_g^j/(1 - s_g^j)$ of the revenues from sales. We divide by the tariff to convert each expenditure amount into the value of production.

In the same manner, the total value of the production of composite intermediates from sector j in a location g has to be equal to a subsidy-weigted fraction (determined by the γ_g^{jk}s) of the expenditure on region g's intermediate goods across sectors and locations. In particular,

$$P_g^{\mathcal{M}j} Q_g^{\mathcal{M}j} = \sum_{k=1}^{J} \frac{\gamma_g^{jk}}{1 - s_g^j} \sum_{i=1}^{G} \frac{x_i^k \pi_{ig}^k}{1 + \tau_{ig}^k}. \tag{29}$$

Notice that market clearing conditions (28) and (29) imply as well that the intermediate goods market clears.

Employing again a production-expenditure equality, market clearing in the location g's final-goods market requires that the value of the sector-j final-goods produced in g equals the consumption expenditure across regions on final products from that location. Taking into account that the revenues from the production activity of the final-product sector fully goes to pay for the intermediate goods used as inputs, we can write the market clearing condition as:

$$x_g^j - \frac{P_g^{\mathcal{M}j} Q_g^{\mathcal{M}j}}{1 - \mathfrak{s}_g^k} = \frac{1}{1 - \mathfrak{s}_g^k} \sum_{i=1}^{G} \frac{X_i^j \Pi_{ig}^j}{1 + T_{ig}^j}. \tag{30}$$

The left hand side of equation (30) subtracts the value of materials to provide just the amount of expenditure in intermediate goods satisfied by final-goods producers. The subsidy $\mathfrak{s}_g^k$ is in the equation because the expenditure on inputs, x_g^j, equals the market revenues—given by the terms affected by the sum operator—plus the subsidies received by the industry.

Note that consumers' expenditure on sector-j products in region-i is a fixed fraction α_i^j of their income. Hence,

$$X_i^j = \alpha_i^j y_i N_i; \tag{31}$$

where income per capita y_i, given by equation (9), is a function of tariff revenues. We can now write those revenues using the notation introduced previously as:

$$F_g = \sum_{j=1}^{J} \sum_{i=1}^{G} \left(\tau_{gi}^j \frac{x_g^j \pi_{gi}^j}{1 + \tau_{gi}^j} + T_{gi}^j \frac{X_g^j \Pi_{gi}^j}{1 + T_{gi}^j} \right). \tag{32}$$

Moving next to the determination of the trade balance, we consider that the regional trade deficit $\tilde{D}_g$ is given by the sum of the sectoral deficits, $\tilde{D}_g^j$. The sectoral deficit $\tilde{D}_g^j$ equals the value of the region g's imports of industry-j goods from all other locations minus the value of exports of sector-j products from location g to all other locations. This is equivalent to imposing that the deficit is given by the difference between total expenditure by region g on sector-j intermediate and final products net of tariffs and the total value of production of industry-j intermediate and final goods in location g. More specifically,

$$\tilde{D}_g^j = \sum_{i=1}^{G} \left(\frac{x_g^j \pi_{gi}^j}{1 + \tau_{gi}^j} + \frac{X_g^j \Pi_{gi}^j}{1 + T_{gi}^j} \right) - \sum_{i=1}^{G} \left(\frac{x_i^j \pi_{ig}^j}{1 + \tau_{ig}^j} + \frac{X_i^j \Pi_{ig}^j}{1 + T_{ig}^j} \right). \tag{33}$$

The second parenthesis gives the value of production by adding across locations the amount spent on products from the sector-region pair (j, g) net of tariffs.

Therefore, trade balance in location g implies the the sum of the sectoral trade deficits must equal the regional one, which means

$$\tilde{D}_g = \sum_{j=1}^{J} \tilde{D}_g^j. \tag{34}$$

It can be shown that the trade balance condition, equation (34) implies that the labor market clears, that is, equation (28).

Finally, we allow for the possibility that the regional budget deficit, denoted by $\bar{D}_g$, is not zero. Therefore, the following condition must hold:

$$\bar{D}_g = \sum_{j=1}^{J} \sum_{i=1}^{G} \left(\frac{s_g^j}{1 - s_g^j} \frac{x_i^j \pi_{ig}^j}{1 + \tau_{ig}^j} + \frac{\mathfrak{s}_g^j}{1 - \mathfrak{s}_g^j} \frac{X_i^j \Pi_{ig}^j}{1 + T_{ig}^j} \right) + \sum_{j=1}^{J} \frac{\mathfrak{s}_g^j}{1 - \mathfrak{s}_g^j} P_g^{\mathcal{M}j} Q_g^{\mathcal{M}j} - \tau_g N_g. \tag{35}$$

That is, if the expenditure in subsidies is larger than the taxes collected to finance them, there will be a positive budget deficit.

3.1.9 Equilibrium system in relative changes

As in Caliendo and Parro (2014), we solve the model in changes. Let us denote a proportional change in a variable with a hat ($\hat{\ }$) and the value of the variable next period with a prime ($'$). Then, for example, $\hat{\tau}_{gi}^j = \tau_{gi}^{j\prime}/\tau_{gi}^j$. The exogenous shocks that we will consider correspond to new tariffs, $\tau_{gi}^{j\prime}$ and $T_{gi}^{j\prime}$, new subsidies to firms, $s_g^{j\prime}$ and $\mathfrak{s}_g^{j\prime}$, supply-chain disruptions proxied by changes in the trade costs, $\hat{d}_{gi}^j$ and $\hat{\mathfrak{d}}_{gi}^j$ for $g \neq i$, local production restrictions proxied by $\hat{d}_{gg}^j$ and $\hat{\mathfrak{d}}_{gg}^j$, and confinement policies captured by new stocks of available labor in the region, L_g'.

Equations (12) and (18) imply that the gross growth rate in the cost of the intermediate-goods input bundle equals

$$\hat{b}_g^j = \left(\frac{1 - s_g^{j\prime}}{1 - s_g^j} \right) \hat{w}_g^{\gamma_g^j} \prod_{k=1}^{J} \left(\hat{B}_g^k \right)^{\gamma_g^{kj}}. \tag{36}$$

In turn, combining expressions (23) and (25) obtains the change in the cost of the final-goods input bundle and the export shares of intermediate products as

$$\hat{B}_g^j = \left(\frac{1 - \mathfrak{s}_g^{j\prime}}{1 - \mathfrak{s}_g^j} \right) \left[\sum_{i=1}^{G} \pi_{gi}^j \left(\hat{b}_i^j \hat{\kappa}_{gi}^j \right)^{-\theta^j} \right]^{-1/\theta^j} \tag{37}$$

and

$$\hat{\pi}_{gi}^j = \left(\frac{\hat{b}_i^j \hat{\kappa}_{gi}^j}{\hat{B}_g^j} \right)^{-\theta^j}, \tag{38}$$

respectively; where $\hat{\kappa}^j_{gi} = \left(1+\tau^{j\prime}_{gi}\right)\hat{d}^j_{gi}/\left(1+\tau^j_{gi}\right)$.The gross growth rate in the sectoral price index and the final-good export shares are delivered by equations (24) and (26) as

$$\hat{P}^j_g = \left[\sum_{i=1}^{G} \Pi^j_{gi}\left(\hat{B}^j_i \hat{K}^j_{gi}\right)^{-\Theta^j}\right]^{-1/\Theta^j} \tag{39}$$

and

$$\hat{\Pi}^j_{gi} = \left(\frac{\hat{B}^j_i \hat{K}^j_{gi}}{\hat{P}^j_g}\right)^{-\Theta^j}, \tag{40}$$

respectively; where $\hat{K}^j_{gi} = \left(1+T^{j\prime}_{gi}\right)\hat{\mathfrak{d}}^j_{gi}/\left(1+T^j_{gi}\right)$.

Market clearing conditions can be employed to obtain the future values of the expenditure variables as a function of the above changes. In particular, market clearing for final-goods, equations (29) and (30), implies that region g's next-period expenditure in intermediate goods from sector j is given by:

$$x^{j\prime}_g = \frac{1}{1-\mathfrak{s}^{j\prime}_g}\left(\sum_{k=1}^{J}\sum_{i=1}^{G}\frac{\gamma^{jk}_g}{1-s^{j\prime}_g}\frac{x^{k\prime}_i\pi^{k\prime}_{ig}}{1+\tau^{k\prime}_{ig}} + \sum_{i=1}^{G} X^{j\prime}_i \frac{\Pi^{j\prime}_{ig}}{1+T^{j\prime}_{ig}}\right). \tag{41}$$

Notice that $\pi^{k\prime}_{ig}$ and $\Pi^{j\prime}_{ig}$ can be written as $\pi^k_{ig}\hat{\pi}^k_{ig}$ and $\Pi^j_{ig}\hat{\Pi}^j_{ig}$, respectively.

From equations (9), (29), (31), (32) and (35), next-period's expenditure in final goods from sector j equals:

$$X^{j\prime}_g = \alpha^j_g\left[L^\prime_g w^\prime_g + \sum_{k=1}^{J}\sum_{i=1}^{G}\left(\tau^{k\prime}_{gi}\frac{x^{k\prime}_g\pi^{k\prime}_{gi}}{1+\tau^{k\prime}_{gi}} + T^{k\prime}_{gi}\frac{X^{k\prime}_g\Pi^{k\prime}_{gi}}{1+T^{k\prime}_{gi}}\right) + \tilde{D}^\prime_g - \tau^\prime_g N_g\right]; \tag{42}$$

where

$$\tilde{D}^\prime_g = \sum_{j=1}^{J}\sum_{i=1}^{G}\left(\frac{x^{j\prime}_g\pi^{j\prime}_{gi}}{1+\tau^{j\prime}_{gi}} + \frac{X^{j\prime}_g\Pi^{j\prime}_{gi}}{1+T^{j\prime}_{gi}}\right) - \sum_{j=1}^{J}\sum_{i=1}^{G}\left(\frac{x^{j\prime}_i\pi^{j\prime}_{ig}}{1+\tau^{j\prime}_{ig}} + \frac{X^{j\prime}_i\Pi^{j\prime}_{ig}}{1+T^{j\prime}_{ig}}\right). \tag{43}$$

Again, we can write $w^\prime_g$ as $w_g\hat{w}_g$ so that it becomes a function of the changes determined by previous equations in the system.

The system formed by equations (36) to (43) is undertermined because the number of unknows is equal to the number of equations plus one. In order to solve it, Caliendo and Parro (2014) assume that the economy's trade deficit in each location g is exogenous. We, on the other hand, allow for the trace deficit to be determined by the model and, instead, required that the wage rate does not vary. This looks to us more appropriate for the problem that we analyze.

Equations (36) to (43) imply that we do not need to calibrate fundamental productivities and trade costs to solve the system. We simply start from a baseline scenario that consists of initial data on regional wages, labor, and trade and budget deficits $\{w_g, L_g, \tilde{D}_g, \bar{D}_g\}^G_{g=1}$, pairwise regional expenditure shares and tariffs in every sector $\{\pi^j_{gi}, \Pi^j_{gi}, \tau^j_{gi}, T^j_{gi}\}^{G,G,J}_{g=1,i=1,j=1}$, and the assumption of no subsidies for firms, $s^j_g = \mathfrak{s}^j_g = 0$. We also need to assign values to the labor share in gross output (γ_g^j), the share of intermediate goods from sector k employed in the production of sector j (γ_g^{jk}), the share of consumption expenditure on sector-j goods (α_g^j), and the shape parameters θ^j and Θ^j of the Fréchet distributions. With that information on our hands, we consider shocks on the values τ'_{gi}, T'_{gi}, $s_g^{j\prime}$, $\mathfrak{s}_g^{j\prime}$, $\hat{d}_{gi}^j$, $\hat{\mathfrak{d}}_{gi}^j$ and/or L'_g, and solve the system going through the following steps.

1. Assume $\hat{w}_g = 0$ for all g.
2. From equations (36) and (37) obtain $\{\hat{b}_g^j, \hat{B}_g^j\}_{g=1,j=1}^{G,J}$.
3. Once we know the cost of the unitary input bundles, we recover the values of $\{\hat{P}_g^j, \hat{\pi}_{gi}^j, \hat{\Pi}_{gi}^j\}$ for all $g \in \{1,\dots,G\}$ and $j \in \{1,\dots,J\}$ from equations (39) to (40).
4. Obtain $\{x_g^{j\prime}, X_g^{j\prime}\}_{g=1,j=1}^{G,J}$ using (41) and (42).

The above implies that, in this economy, an equilibrium in relative changes can be defined as follows. Given the new value of the regional labor supply $\{L_g\}_{g=1}^{G}$, regional deficits $\{\tilde{D}'_g, \bar{D}'_g\}_{g=1}^{G}$, and pairwise regional government policies in every industry $\{\tau_{gi}^{j\prime}, T_{gi}^{j\prime}\}_{g=1,i=1,j=1}^{G,G,J}$, a competitive equilibrium is a set of changes in intermediate-good and final-product price indices in for each sector-location pair $\{\hat{B}_g^j, \hat{P}_g^j\}_{g=1,j=1}^{G,J}$, and pairwise regional expenditure shares in every sector $\{\hat{\pi}_{gi}^j, \hat{\Pi}_{gi}^j\}_{g=1,i=1,j=1}^{G,G,J}$, in addition to new values of the total sector-location expenditure volumes $\{x_g^{j\prime}, X_g^{j\prime}\}_{g=1,j=1}^{G,J}$, such that the optimizing conditions for households, intermediate-product manufacturers, final-good firms and material producers—which are reflected in equations (12), (18), (23) to (26) and (31)—hold, and market clearing in all markets is achieved through conditions (29), (30) and (33).

3.2 Phase 2: Infection Dynamics

The dynamics take place at the *local* level but we allow for possible contagions across locations depending on effective distance. Typically, epidemiology models characterize the transitions from one state to another with exogenously given probabilities that refer to the characteristics of the particular infection. Here, instead, we assume that transition probabilities depend on two factors, one exogenous that captures the characteristics of the infection, and an endogenous geographic component that captures how more economically active locations can be more prone to infections since they have more connections with the rest of locations.

People that work face-to-face, people that work telematically, and people that do not work have different probabilities of catching the disease due to their different number of encounters with other people. Additionally, individuals that have recovered from the disease or have been vaccinated can have a lower probability of becoming infected. We assume that all the infected, regardless of whether they are in hospital or not, are able to pass the disease to workers; obviously, if the infected is in a hospital, they can pass the disease mainly to health workers.

We consider two scenarios where people can become infected. First, infections occur *locally* through social interactions not related to market activities, like for example visiting relatives at home or walking in the streets. Second, the virus can be transmitted through a *market related* activity, what we call the *geographic component*, such as workers producing output, consumers enjoying a beverage in a cafeteria, or product trade. Within this second component, the movement of goods and services within and between regions can also be an important vector for the transmission of the disease, because some degree of human interaction is needed to arrange those transactions. For example, when infected people buy tourism or via infected truck drivers. Actually, Oster (2012) finds that doubling exports increases HIV infections by 10-70% through truckers in Africa. Importantly, truck transportation is responsible for the movement of 80% of the world's goods. In the same vein, Adda (2016) finds that the expansion of transportation networks and inter-regional trade explains an important part of the prevalence of infection diseases in France.

Locally, susceptible individuals get infected with probability denoted by $(1-\kappa)\rho_g$; where κ captures the proportion of infections that arise in market-related contexts (trade or production) and is time-invariant. The time-varying probability ρ_g provides the likelihood that a susceptible individual gets the disease if an infected agent is met. The parameter ρ_g is affected by local policies, local behaviors, and other non-production related characteristics. The weight of the geographic component, in turn, depends on the level of market activity. This can be captured by the expenditure variables x_{ig}^j and X_{ig}^j. Hence, the dynamics for infected people can be written as:

$$I_g' = \underbrace{(1-\varphi)I_g}_{\text{Infected not becoming resolving}} + S_g\Phi_g; \tag{44}$$

where the term Φ_g is given by

$$\Phi_g = \underbrace{(1-\kappa)\rho_g\frac{I_g}{N_g}}_{\text{Local Component}} + \underbrace{\kappa\left(\sum_{i=1}^{G}\rho_i\frac{I_i}{N_i}\Lambda_i\tilde{X}_{ig}\right)}_{\text{Geographic Component}}; \tag{45}$$

and the coefficient φ gives the fraction of infected that become resolving every period.

According to motion equation (44), the number of infected people tomorrow depends on infected people today net of those that become resolving cases. The equation also considers that the susceptible can catch the disease. As expression (45) specifies, this can occur through the local and the geographic components. The strength of the latter depends on the contagion probability and the prevalence of the disease in the trade partner and also on the relative level of human interactions in transactions. In particular, the term $\tilde{X}_{ig}$ represents the level of market interaction between any two regions i and g, and is given by:

$$\tilde{X}_{ig} = \frac{\sum_{j=1}^{J}\left(x_{ig}^{j} + x_{gi}^{j} + X_{ig}^{j} + X_{gi}^{j}\right)}{\sum_{h=1}^{G}\sum_{k=1}^{J}\left(x_{hg}^{k} + x_{gh}^{k} + X_{hg}^{k} + X_{gh}^{k}\right)} \tag{46}$$

It says that the human-interaction level between two economies i and g is a function of bilateral imports and exports if two different locations are involved or a function the local expenditure volumes if market activity is fully local. Notice that the bilateral trade volumes in equation (45) are weighted by a region variable Λ_i that controls for the degree of telematic work, among other things.[6]

The following equations, along with equation (44), describe the full epidemiological model:

$$S_g' = (1 - \lambda_g - \Phi_g)S_g + \alpha^V V_g + \alpha^C C_g \tag{47a}$$

$$V_g' = (1 - \alpha^V)V_g + \lambda_g S_g \tag{47b}$$

$$R_g' = \varphi I_g + (1 - \xi)R_g \tag{47c}$$

$$C_g' = (1 - \alpha^C)C_g + (1 - \delta)\xi R_g \tag{47d}$$

$$F_g' = F_g + \delta\xi R_g \tag{47e}$$

$$N_g' = N_g - \delta\xi R_g \tag{47f}$$

The parameter λ_g represents the fraction of the susceptible that are vaccinated during the period in location g; α_c and α_v are the fraction of the recovered and the vaccinated that fully lose immunity, respectively; the parameter ξ reflects the fraction of cases that resolve in a given period, and therefore, its inverse pins down the average number of periods it takes for a case to resolve; and φ relates to the average number of days $(1/\varphi)$ a person is infectious.

Equation (47a) says that the size of the susceptible population decreases with the fraction λ_g that receives the vaccine and the fraction Φ_g that gets infected by the Covid-19 virus, but rises with the recovered and vaccinated that lose their immunity. The vaccinated population, equation (47b), increases with the fraction of the susceptible that receive the vaccine and decreases with the vaccinated individuals that lose immunity. In equation (52), in turn, a fraction φ of infected individuals become resolving, and a fraction ξ of cases are resolved. The number of recovered individuals, equation (47d), evolves in a similar way as the one of the vaccinated: a fraction α_c lose their immunity and some of the resolving, among the fraction δ that survives, recover during

[6]It can be show that the basic reproduction number of the disease, $\mathcal{R}_0$, increases in our setup with the level of trade integration between two regions, $\tilde{X}_{ig}$. See appendix A for the details. The coefficient $\mathcal{R}_0$ represents the average number of secondary infections produced by a typical case of an infection in a population where everyone is susceptible.

the period. The evolution of the stock of fatalities (F_g) is simple, (47e) implies that the new deaths come from the fraction ($\delta\xi$) of resolving that resolve and die. Finally, the evolution of the region's population is given by equation (47f), which implies that a fraction $\delta\xi$ of the resolving cases die.

4 Calibration

The main source for the calibration of the economic part of the model is Thiessen (2020), which offers the Rhomolo-MRIO Tables for 2013 published by the European commission. The dataset provides input-output tables for a set of 268 regions that include 267 EU28 NUTS2-2010 areas plus the rest of the world (ROW). Nevertheless, due to the lack of sufficiently disaggregated data for the disease variables, we need to aggregate some locations to the NUTS1 and country levels. After doing so, we are left with 230 regions (see Table 1). The numbers are disaggregated into ten main sectors of activity belonging to the NACE Rev2 classification (see Table 2). A summary of the data sources employed for the calibration of both the economic and disease parameters—and their values in some cases—are provided in Table 3.

From Thiessen (2020), we also compute α_g^j, that is, the shares of the different sectors in total consumption expenditure in each location. The same dataset allows deriving estimates of the share of value added on gross output, γ_g^j, and the expenditure share of each material employed in the input composite of the intermediate good produced by other industries, γ_g^{kj}.[7]

The sector-specific shape parameters θ^j and Θ^j of the Fréchet distributions related to the productivity variables z_g^j and Z_g^j, respectively, are obtained as follows. Consider two regions, i and g, and the bilateral trade expenditures between the two, x_{gi}^j, x_{ig}^j, X_{gi}^j and X_{ig}^j. Recall that expenditure shares $\pi_{gi}^j = x_{gi}^j / x_g^j$ and $\Pi_{gi}^j = X_{gi}^j / X_g^j$ are given in equilibrium by equations (25) and (26). These expressions imply that we can write:

$$\frac{x_{gi}^j \, x_{ig}^j}{x_{gg}^j \, x_{ii}^j} = \left(\frac{\kappa_{gi}^j \, \kappa_{ig}^j}{\kappa_{gg}^j \, \kappa_{ii}^j} \right)^{-\theta^j}, \tag{48}$$

and

$$\frac{X_{gi}^j \, X_{ig}^j}{X_{gg}^j \, X_{ii}^j} = \left(\frac{K_{gi}^j \, K_{ig}^j}{K_{gg}^j \, K_{ii}^j} \right)^{-\theta^j}. \tag{49}$$

Equations (48) and (49) provide gravity equations for intermediate and final products, respectively. They present bilateral trade expenditures as a function of bilateral trade costs. Equations (19) and (20) say that trade costs are composed of tariffs and iceberg costs. We assume, for the

[7]Due to the large number of observations, these and other parameter and variable values are not reported in the paper. They are available from the authors upon request.

only purpose of estimating the trade shares, that $d^j_{gi} = \mathfrak{d}^j_{gi} = v_{gi}\ e^{\mu^j_g + \eta^j_i + \varepsilon^j_{gi}}$; where $v_{gi} = v_{ig}$ represents symmetric bilateral trade costs like distance (geographical, language, etc...) or belonging to a certain trade agreement; μ^j_g and η^j_i capture sector-specific fixed effects in the importer and exporter regions, respectively; and ε^j_{gi} is a random disturbance. Substituting those expressions for trade costs into (48) and (49), equalizing tariffs to zero and taking logs, we obtain:

$$\ln\left(\frac{x^j_{gi}\ x^j_{ig}}{x^j_{gg}\ x^j_{ii}}\right) = -\theta^j \ln\left(\frac{v_{gi}v_{ig}}{v_{gg}v_{ii}}\right) + \tilde{\varepsilon}^j_{gi};$$

and

$$\ln\left(\frac{X^j_{gi}\ X^j_{ig}}{X^j_{gg}\ X^j_{ii}}\right) = -\Theta^j \ln\left(\frac{v_{gi}v_{ig}}{v_{gg}v_{ii}}\right) + \tilde{\varepsilon}^j_{gi};$$

where $\tilde{\varepsilon}^j_{gi} = \varepsilon^j_{gi} + \varepsilon^j_{ig} - \varepsilon^j_{gg} - \varepsilon^j_{ii}$. Hence, all asymmetric components of the iceberg costs (μ^j_g, μ^j_i, η^j_g and η^j_i) have cancelled out. In addition, we have equalized tariffs to zero because, in the estimation, we use data on export spending for the EU28 in 2013 from Thiessen (2020) but exclude the flows from and to the rest of the world; clearly, trade among EU members are not subject to tariffs or other trade restrictions.

As proxy for the symmetric component of the bilateral trade costs, we employ distance between regions obtained from Persyn et al. (2020). This dataset gives estimates of different distance measures between EU regions at the NUTS2 level. We choose the distance measure that provides arithmetic averages over the geodesic distance between many centroids for each region-pair. Each region have more than on centroid and then $v_{gg} > 1$. In the estimation, we use data on expenditure variables (x^j_{gi} and X^j_{gi}) from the original 267 European regions considered in Thiessen (2020) to maximize the amount of information. The results of the estimation of the trade elasticities are presented in Table 4. The estimates range from 1.99 to 3.09 for intermediate goods and from 1.94 to 3.09 for final products. The smallest elasticity corresponds to construction (sector C), and the largest to public administration, defence, education, human health and social work activities (sectors O_Q).

We now turn to the parameters that govern the disease dynamics. We set the values for Λ_g from Dingel and Neiman (2020). In particular, we estimate the percentage of workers in each sector that can work from home ς_j and then, for each region, we compute Λ_g as

$$\Lambda_g = 1 - \sum_{j\in J} \varsigma_j \frac{x^j_g + X^j_g}{\sum_{k\in J} x^k_g + X^k_g}$$

which is a weighted average where the weights are sectoral expenditure shares. This takes into account the sectoral composition of each region.

Parameter κ comes from Eichenbaum et al. (2020) who estimate 17% of infections related to work environments. We take φ, ξ and δ from Fernández-Villaverde and Jones (2020). The parameter φ is equalized to 0.125, which implies that an individual is infectious for 8 days, and ξ to 0.143 so that the average case takes 15 days to fully resolve (8 days infectious plus 7 of resolving). The mortality rate δ is taken which is set to 1%.

Next, since we focus on the first wave, we equalize to zero the vaccination rate λ_g and the immunization loss for vaccinated α^V. The evidence on reinfection rates for COVID-19 is still unclear. Regarding reinfection among those not vaccinated, Sheehan et al. (2021) estimate that the protection from getting infected ranges from $81.8-84.5\%$. Taking into account this evidence, we fix $\alpha^C = 0.168$ which implies a protection from the infection of 83.15%.

Finally, we recover the time-variant ρ_g, that is, the probability that a susceptible individual gets the disease.[8] Because some regions do not have data on Covid-19 daily deaths (see Table 5 for details), we need to split our sample in two groups. The first group is composed of those areas that do report daily deaths. The second one, in turn, is the set of regions that only report confirmed cases. For those regions that report deaths, we extend the approach suggested by Fernández-Villaverde and Jones (2020), which essentially boils down to obtaining ρ_g as a residual using data on deaths only. This method is explained in detailed in appendix B.[9]

However, sometimes in a region, we encounter three consecutive days with zero deaths and the method breaks down. When this occurs, we estimate a constant infection rate $\bar{\rho}_g$ for the region that presents the problem as follows. We first make $\kappa = 0$ to eliminate the geographic component so that we can obtain a $\bar{\rho}_g$ in isolation from other regions. Then, we estimate $\bar{\rho}_g$ by NLLS so as to minimize the distance of the predicted deaths from the actual death observations. This estimated average infection rate is assigned ($\rho_g = \bar{\rho}_g$) only to the periods in which it is not possible to recover it due to the consecutive-zeros problem.

For the regions that do not report daily deaths, we give daily values to ρ_g based on the reported number of daily infections. To do that, we again first omit the geographical components (i.e., $\kappa = 0$), and from equations (44) and (45) recover, for each day and region, a preliminary ρ_g from the infection data. This preliminary ρ_g serves to generate the necessary time series of predicted fatalities F_g from the system of equations (44) to (47e). Once we have the estimated deaths, we follow the method described in appendix B to get ρ_t that will be used during the simulations.

[8]For the calibration of the remaining disease parameters and initial values, ROW was assumed to be composed by China, the U.S. and Switzerland. This means that for both, the EU27 and the UK, we consider at least 70% of the trade volumes with other areas.

[9]In the calibration of ρ_g, we eliminate the geographical component, that is, take $\kappa = 0$. The reason is that, in many periods, the large number of zero deaths makes the system where the $\{\rho_g\}_{g=1}^{G}$ are obtained jointly (because of the geographical component) indeterminate. This problem could be partially solved through singular value decomposition and applying a least-squares method. However, the gap between predicted and actual deaths was always significantly worse when using this alternative procedure.

In order to start the simulations, we need initial values for different variables. Tables 6 and 7 provide some of those initial values for different economic and disease related variables, respectively. The population size N_g at the beginning of the pandemic in each region comes from the same sources as deaths (see Table 5). To be consistent with the input-output data, the rest of numbers are extracted from the year 2013. We pick the expenditure shares of intermediate goods and final products by sector, origin and destination, π^j_{gi} and Π^j_{gi}, from Thiessen (2020). The number of workers, L_g, are obtained from different sources. In particular, for the EU28, we use employment by NUTS 2 regions from regional labour statistics, Eurostat. For ROW, we take the number of persons engaged from Penn World Tables, 10.0.

Wages, w_g, are calculated as total compensation of employees divided by the employment figures. Total compensation of employees for the EU27 group (EU28 minus the United Kingdom) comes from the Eurostat regional accounts data; whereas for the UK, we get them from the gross annual pay for all employee jobs reported by Annual Survey of Hours and Earnings. For ROW, compensation of employees are directly taken from Thiessen (2020). Lump-sum taxes τ_g are calibrated so as to reproduce the observed total expenditures on final products by region and sector, X^j_g, provided by Thiessen (2020).

Subsidies for intermediate goods and final-good products/materials, s^j_g and $\mathfrak{s}^j_g$, respectively, are equalized to zero. Bilateral ad-valorem tariff for intermediate and final goods, τ^j_{gi} and T^j_{gi}, respectively, are zero among EU members. The only tariffs different from zero are the ones related to ROW. We assign values to the different industries using information from Eurostat (2017) on average import tariffs imposed by the EU28 to other countries in 2013 and WITS - UNCTAD TRAINS information (see appendix for details).

5 Results

We focus on the first wave of the Covid-19 pandemic, and more specifically, in the period that goes from February 25 to July 15, 2020. First, we take a look at the fatality data and the calibrated ρ_g. Figure 1 provides the total daily number of deaths in the European Union (EU27) and in the UK. This number in our smoothed time series reached a maximum values of 2,867 in the EU27 on April 4^{th}, and 887 in the UK on April 11^{th}. That is, the pandemic in the UK evolved with a one-week lag compared to the European Union. Nevertheless, even the death events were larger in continental Europe, the incidence of the disease was actually larger in the UK. We can observe this fact in Figure 2 that reports the number of deaths per 100,000 inhabitants. In the UK, this ratio reached 1.25, whereas in the EU27 its maximum was a bit less than half that number, in particular it was 0.61.

Figure 3 presents the average value of the parameter ρ_g across NUTS2 regions. Remember that this parameter is calibrated as a residual, and therefore, its values capture the disease ecology but also the effect of the policies applied to fight the pandemic. We can see in Figure 3 that the probability of infection reached higher values in the UK than in the European Union. The maximum, in particular, was 0.20 on March 21^{st} for the former economy and 0.14 on March 22^{nd} for the latter. However, we can also see that the reduction was faster and deeper in the UK than in the EU27. That is, policies seem to have been more successful in the UK, maintaining after April 16th a gap in favor of the UK of about 2 percentage points.

Let us now have a more disaggregated view of the death data in the UK. Figure 4 plots the number of deaths in each of the 37 NUTS2 regions in the UK. The largest number of daily cases was achieved in Inner London-East (UKI2), Greater Manchester (UKD3) and West Midlands (UKG3) with 118, 64 and 57 deaths in one day, respectively. The lowest daily numbers, on the other hand, took place in North Eastern Scotland (UKM5), Highlands and Islands (UKM6) and Northern Ireland (UKN0) with 3, 3 and 4 cases, respectively.

Even though the number of deaths and their relative magnitude per 100,000 inhabitants show a high correlation of 0.561, they do not correlate perfectly. In the second column of results in Table 8, we see that the largest volumes of deaths per 100,000 inhabitants are found in Greater Manchester (UKD3), Cheshire (UKD6), Trees Valley and Durham (UKC1) and West Midlands (UKG3) with rates equal to 93, 90, 87 and 87; and the lowest in Northern Ireland (UKNO), Dorset and Somerset (UKK2) and Devon (UKK4) where these rates were 6, 19 and 22, respectively.

Our next task is analyzing what the predictions of the model say about the impact of the policy measures implemented during the first wave and captured by the evolution of the parameter ρ_g. We start by looking at how the model does at matching the fatality data. Figure 5 shows that the model predictions follow well the trend and its changes in the data. Nevertheless, they tend to underestimate the number of deaths. Comparing columns one and three in Table 8, we can see that this generates an error in the predicted total number of deaths of 19.5% and 24.8% for the European Union and the United Kingdom, respectively. This is due to the method followed to calibrate the parameter ρ_g, which does not consider the geographic component of the infection (see appendix for details).

The first question that we ask is what would have been the cost for the economy in terms of deaths if no policy had been implemented. At the regional level, the parameter ρ_g reaches it largest values at the beginning of the infection in the corresponding area, and then goes down due to the policy actions implemented. Hence, in order to answer the above question, we let the parameter ρ_g remain constant at its average over the first ten days during which region g reports fatalities. The purpose of averaging out over ten days is reducing measurement error concerns.

Table 8 in the columns labeled as "Predicted deaths with ρ constant" gives the results from this exercise. Without the policy reaction, deaths in the European Union would have been 4,545,222 instead of the predicted 107,112, and 1,248,078 instead of 30,571 in the UK. Which represent an increase rate of 4,143% and 3,983%, respectively. In terms of the lives saved per 100,000 inhabitants, the average for the EU27 and the UK equal 202 and 1718, respectively. That is, again the impact looks stronger in the UK. Across NUTS2 UK regions, there is a relatively high correlation of 0.668 between the number of deaths and the live saved by policies. More specifically, the largest effect is found in Berkshire, Buckinghamshire and Oxfordshire (UKJ1) where 2654 lives per 100,000 inhabitants were saved by the policy measures. Other areas where more than 2000 lives per 100,000 inhabitants were saved include Cheshire (UKD6), Derbyshire and Nottinghamshire (UKF1), Greater Manchester (UKD3), Inner London-East (UKI2), West Midlands (UKG3) and Essex (UKH3). The smallest impact, in turn, is found in Lincolnshire (UKF3), North Eastern Scotland (UKM5) and Dorset and Somerset (UKK2), where the lives saved are between 849, 861 and 903 per 100,000 inhabitants, respectively.

In this paper, we are specially interested in measuring the impact of the economic links in the pandemic. Let us start by looking at the weight of trade with different locations in each of the UK regions. Table 9 says that the largest share in trade is UK based. Intra-region and cross-UK-region trade accounts for between 83.0% and 96.2% of total trade. Whether the former form of trade or the latter one dominated varies widely across regions. For example, Cheshire (UKD6) is the one that shows the largest reliance in domestic trade: 50.6% is trade within the region and 25.4% comes from flows with other UK areas. Lincolnshire (UKF3) is, on the other extreme, the one that relies the less from intra-region flows, only 28.7%, whereas its inter-regional trade with the rest of the UK accounts for 66.1% of total trade. Trade flows with the European Union also vary significantly across UK regions. The largest shares of 7.6% and 7.9% are shown by Inner London East and West (UKI1 and UKI2), whereas the lowest of 3.2% is shown by Eastern Scotland (UKM2). These results tell us that trade across regions may have had an important effect on the spread of the disease.

A first assessment of the effect of these economic links is provided in the fourth column of results in Table 8. It gives the percentage contribution of the Geographic component in equation (45) to the generation of infected individuals, and therefore, to the number of fatalities. Recall that the Geographic component is the one that collects the impact of all economic activity. The weight of this component in total deaths is, on average, around 10%, and more specifically, 10.2% in the European Union and 9.7% in the UK. Across UK regions, it reaches the highest values of 19.6 percent in Inner London-East (UKI2), 17.0% for Eastern Scotland (UKM2) and 16.8% for Devon. The smallest one, 7.8%, corresponds to Kent (UKJ4) and North Eastern Scotland (UKM5).

The geographic component is also affected by domestic economic activity. To get a closer look at the effect of the trade relations with other nations. We consider the effect of maintaining ρ_g constant in the EU27 but not in the UK. This will give us an idea of the impact of the applied European-Union anti-Covid-19 policies on the UK prevalence. This effect in our model fully runs through economic activity. The first three columns in Table 10 provide the results of this experiment. Without the policies implemented in the EU27, the number of deaths in the UK would have been a 80% larger. The lives saved by those policies amount to 24,434 or 34 per 100,000 inhabitants.

By region, Highlands and Islands (UKM6) are the one that was benefitted the most, with lived saved per 100,000 inhabitants equal to 76. Then, Cornwall and Isles of Scilly (UKK3), Cumbria (UKD1), Northern Ireland (UKN0), North Eastern Scotland (UKM5) and Lincolnshire (UKF3) saved more than 50 lives each. The ones that benefitted the less were Greater Manchester (UKD3), West Yorkshire (UKE4), Gloucestershire, Wiltshire and Bristol/Bath area (UKK1) and West Midlands (UKG3), for which the EU27 policies saved less than 25 lives.

The last three columns in Table 10 focus exclusively on the policies implemented in the UK. They show the results when we assume that ρ_g changes only in non-UK regions. They say that UK anti-Covid-19 measures saved 50,620 lives in the European Union, which represents two lives per 100,000 inhabitants. In the UK, this number is much larger; in particular, they saved a total of 1,204,239 lives or 1,700 per 100,000 inhabitants. Berkshire, Buckinghamshire and Oxfordshire (UKJ1) was the most benefitted, with 2,649 lives saved per 100,000 inhabitants. It was followed by Cheshire (UKD6), Greater Manchester (UKD3), Derbyshire and Nottinghamshire (UKF1), Inner London-East (UKI2), West Midlands (UKG3) and Essex (UKH3); all of them with more than 2,000 lives saved by the fight against Covid-19 in the UK during the first wave. At the bottom of this ranking, we have Lincolnshire (UKF3), North Eastern Scotland (UKM5) and Dorset and Somerset (UKK2) with 808, 818 and 864 lives saved per 100,000 inhabitants, respectively. Interestingly, the correlation across UK regions between the lives saved by EU27 and by UK policies is -0.672. The reason is that the EU27 effect on the UK works exclusively through economic links, whereas the one of UK policy affects the evolution of the disease also through social interaction.

6 Conclusion

We have built a spatial model of trade with supply-chain links across NUTS2 European regions to try to understand the effect of economic links and policies in the spread of the Covid-19 pandemic during the first wave, which goes from the 25^{th} of February to the 15^{th} of July, 2020. Our have mainly focus on this effect within the UK.

During that period, the incidence the disease was larger in the UK than in the European Union. However, we find that the fight to reduce the infection rates was more successful in the former economy than in the latter. More importantly, without the policy reaction in Europe, the number of deaths during the first wave of the pandemic would have been about 4,400,000 larger in the European Union, and about 1,217,000 higher in the UK. In terms of the lives saved per 100,000 inhabitants, the average for the EU27 and the UK equal 202 and 1,718, respectively. On average, the largest gains where in areas where the volume of deaths was higher, like Berkshire, Buckinghamshire and Oxfordshire, Cheshire, Greater Manchester, Inner London-East, West Midlands, and Essex.

In terms of the effect of economic activity to the spread of the disease and the impact of the policy measures, we find that the percentage contribution of the Geographic component to the number of fatalities is, on average, around 10%. Hence, even though family and social interactions have a larger weight, the one of economic activity is also significant. We also find that the number of deaths in the UK in the absence of anti-Covid-19 measures in the European-Union would have been a 80% larger; they saved about 34 lives per 100,000 inhabitants. In turn, UK anti-Covid-19 measures saved 50,620 lives in the European Union, which represents two lives per 100,000 inhabitants. In the UK, this number is much larger; in particular, they saved a total of about 1,200,000 lives or 1,700 per 100,000 inhabitants.

We have just started exploiting the rich structure of the model. There is still much work that can be done to understand the effects of economic links on the spread of the disease and the capacity of the economy to recover from the recession. In future work, we plan to analyze the effect on the more recent evolution of the pandemic and on the prospects of the economy to recover of vaccination policies, telematic work, selected sectoral and regional closures, subsidies and tariffs.

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A The Basic Reproduction Number in Our SVIRCF Model

Following Heffernan et al. (2005), we can write the equation for infected individuals in matrix form as:

$$\mathbf{I}' = (\mathbb{I} + \mathbf{F} - \mathbf{D})\,\mathbf{I}; \tag{50}$$

where $\mathbb{I}$ is the identity matrix, $\mathbf{I}'$ is the vector of infections in each location at time $t+1$, and $\mathbf{F}$ and $\mathbf{D}$ are defined as

$$\mathbf{F} = \begin{pmatrix} (1-\kappa)\rho_1 \frac{S_1}{N_1} + \kappa\Lambda_1\rho_1\tilde{X}_{11}\frac{S_1}{N_1} & \cdots & \kappa\Lambda_g\rho_g\tilde{X}_{g1}\frac{S_1}{N_g} & \cdots & \kappa\Lambda_G\rho_G\tilde{X}_{G1}\frac{S_1}{N_G} \\ \vdots & \ddots & \cdots & \cdots & \vdots \\ \kappa\Lambda_1\rho_1\tilde{X}_{1g}\frac{S_g}{N_1} & \cdots & (1-\kappa)\rho_g\frac{S_g}{N_g} + \kappa\Lambda_g\rho_g\tilde{X}_{gg}\frac{S_g}{N_g} & \cdots & \kappa\Lambda_G\rho_G\tilde{X}_{Gg}\frac{S_g}{N_G} \\ \vdots & \cdots & \cdots & \ddots & \vdots \\ \kappa\Lambda_1\rho_1\tilde{X}_{1G}\frac{S_G}{N_1} & \cdots & \kappa\Lambda_g\rho_g\tilde{X}_{gG}\frac{S_G}{N_g} & \cdots & (1-\kappa)\rho_G\frac{S_G}{N_G} + \kappa\Lambda_G\rho_G\tilde{X}_{GG}\frac{S_G}{N_G} \end{pmatrix}$$

$$\mathbf{D} = \begin{pmatrix} \varphi & \cdots & 0 & \cdots & 0 \\ \vdots & \ddots & \cdots & \ddots & \vdots \\ 0 & \cdots & \varphi & \cdots & 0 \\ \vdots & \ddots & \cdots & \ddots & \vdots \\ 0 & \cdots & 0 & \cdots & \varphi \end{pmatrix}$$

For the two region case, these matrices equal:

$$\mathbf{F} = \begin{pmatrix} (1-\kappa)\rho_1\frac{S_1}{N_1} + \kappa\Lambda_1\rho_1\tilde{X}_{11}\frac{S_1}{N_1} & \kappa\Lambda_2\rho_2\tilde{X}_{21}\frac{S_1}{N_2} \\ \kappa\Lambda_1\rho_1\tilde{X}_{12}\frac{S_2}{N_1} & (1-\kappa)\rho_2\frac{S_2}{N_2} + \kappa\Lambda_2\rho_2\tilde{X}_{22}\frac{S_2}{N_2} \end{pmatrix}$$

$$\mathbf{V} = \begin{pmatrix} \varphi & 0 \\ 0 & \varphi \end{pmatrix}$$

Let us keep focusing on the simplest case of two regions for which the components of $\tilde{X}_{gi}$ do not change over time, neither the parameters regarding the disease ecology. In addition, assume that $S_{m,t} = N_{m,t}$ and there is no vaccine available. Then, we have that the basic reproduction number $\mathcal{R}_0$ is given by the largest eigenvalue of matrix $\mathbf{B} = \mathbf{F}\mathbf{V}^{-1}$. Matrix $\mathbf{B}$ is given by

$$\mathbf{B} = \begin{pmatrix} \frac{\tilde{X}_{11}\kappa\rho\Lambda + \rho(1-\kappa)}{\varphi} & \frac{\tilde{X}_{21}\kappa\rho\Lambda}{\varphi} \\ \frac{\tilde{X}_{12}\kappa\rho\Lambda}{\varphi} & \frac{\tilde{X}_{22}\kappa\rho\Lambda + \rho(1-\kappa)}{\varphi} \end{pmatrix}$$

and the basic reproduction number is given by

$$\mathcal{R}_0 = \frac{\kappa\rho\Lambda\sqrt{\tilde{X}_{11}^2 - 2\tilde{X}_{11}\tilde{X}_{22} + 4\tilde{X}_{12}\tilde{X}_{21} + \tilde{X}_{22}^2}}{2\varphi} + \frac{\rho\left(\tilde{X}_{11}\kappa\Lambda + \tilde{X}_{22}\kappa\Lambda - 2\kappa + 2\right)}{2\varphi}$$

(There seem to be subindices missing in $\rho\Lambda$) which increases with trade integration, since the partial derivatives are increasing in the trade share with the opposite region.

$$\frac{\partial \mathcal{R}_0}{\partial \tilde{X}_{12}} = \frac{\kappa\rho\Lambda\tilde{X}_{21}}{\varphi\sqrt{\tilde{X}_{11}^2 - 2\tilde{X}_{11}\tilde{X}_{22} + 4\tilde{X}_{12}\tilde{X}_{21} + \tilde{X}_{22}^2}} > 0$$
$$\frac{\partial \mathcal{R}_0}{\partial \tilde{X}_{21}} = \frac{\kappa\rho\Lambda\tilde{X}_{12}}{\varphi\sqrt{\tilde{X}_{11}^2 - 2\tilde{X}_{11}\tilde{X}_{22} + 4\tilde{X}_{12}\tilde{X}_{21} + \tilde{X}_{22}^2}} > 0$$

B Parameters for the Evolution of the Disease

In order to calibrate $\{\rho_{gt}\}_{g=1}^{G}$, we follow the method in Fernández-Villaverde and Jones (2020) and recover the parameter from deaths numbers. In addition, to ameliorate possible mismeasurement problems, like for example underreporting during weekends, we first smooth those daily-deaths series using a moving average of seven days and then a Hodrick-Prescott filter with smoothing parameter 850.

This calibration method is applied to our case as follows. Let us add a time index (t) to the different variables for mathematical convenience. Additionally, let us take the convention that Z_t provides the value of an arbitrary variable Z at the end of period t, and that $\Delta Z_{t+1} = Z_{t+1} - Z_t$.[10] Define also $f_{gt+1} \equiv \Delta F_{gt+1}$, that is, the (smoothed) number of people that died on day $t+1$ in region g. For the initial waves of the pandemic, in which there was no vaccine available, we assume $\lambda_g = 0$ for all regions.

From equation (47e), we can solve for R_{gt} in terms of daily deaths as

$$R_{gt} = \frac{f_{gt+1}}{\delta\xi}, \tag{51}$$

which then implies

$$\Delta R_{gt+1} = \frac{\Delta f_{gt+2}}{\delta\xi}. \tag{52}$$

Combining equations (47c) and (52), we can express infected individuals today as a function of future daily fatalities:

$$I_{gt} = \frac{1}{\delta\varphi}\left(\frac{\Delta f_{gt+2}}{\xi} + f_{gt+1}\right). \tag{53}$$

Which implies

$$\Delta I_{gt+1} = \frac{1}{\delta\varphi}\left(\frac{\Delta f_{gt+3} - \Delta f_{gt+2}}{\xi} + \Delta f_{gt+2}\right). \tag{54}$$

Using the ratio of (54) to (53), the growth rate of the infected cases can be obtained as:

$$\frac{\Delta I_{gt+1}}{I_{gt}} = \frac{1/\xi(\Delta f_{gt+3} - \Delta f_{gt+2}) + \Delta f_{gt+2}}{1/\xi\Delta f_{gt+2} + f_{gt+1}}. \tag{55}$$

[10]Notice that the timing convention does not have any important implication for our previous discussion. It would simply mean, for example, that when the susceptible is infected by the virus or vaccinated during period t, it does not develop the disease or gets immunity until period $t+1$; and that, since L_{gt} is then the number of workers available at the end of period t, all the economic activity takes place at the end of each period.

Next, equation (44), letting $G_{gt}(I_{it})$ denote the geographic component in equation (45), delivers

$$(1-\kappa)\rho_{gt} + \frac{\kappa G_{gt}(I_{it})N_{gt}}{I_{gt}} = \frac{N_{gt}}{S_{gt}}\left(\frac{\Delta I_{gt+1}}{I_{gt}} + \varphi\right).$$

Which substituting (53) and (55) becomes:

$$(1-\kappa)\rho_{gt} + \kappa G_{gt}(I_{it})\frac{\delta\varphi N_{gt}}{\left(\frac{\Delta f_{gt+2}}{\xi} + f_{gt+1}\right)} = \frac{N_{gt}}{S_{gt}}\left(\frac{1/\xi(\Delta f_{gt+3} - \Delta f_{gt+2}) + \Delta f_{gt+2}}{1/\xi \Delta f_{gt+2} + f_{gt+1}} + \varphi\right). \quad (56)$$

To get an expression for the evolution of the susceptible as a function of the fatalities, we can use (47a), (45) and (53) to obtain the law of motion for this variable as:

$$S_{gt+1} = S_{gt}\Bigg\{1 - \lambda_{gt} - (1-\kappa)\frac{\rho_{gt}}{\delta\varphi N_{gt}}\left(\frac{\Delta f_{gt+2}}{\xi} + f_{gt+1}\right) + \kappa\left(\sum_{i\in G}\tilde{X}_{ig}l_{it}\rho_{it}\frac{1}{\delta\varphi N_{it}}\left(\frac{\Delta f_{it+2}}{\xi} + f_{it+1}\right)\right)\Bigg\} + \alpha^C C_{gt} + \alpha^V V_{gt}.$$

Note we also need to include the law of motion for vaccinated and recovered individuals which from (47b) and substituting equation (51) into (47d) yield

$$V_{gt+1} = (1-\alpha^V)V_{gt} + \lambda_{gt}S_{gt} \quad (57)$$

$$C_{gt+1} = (1-\alpha^C)C_{gt} + \frac{1-\delta}{\delta}f_{gt+1} \quad (58)$$

Finally, we need initial values for $\{I_{g0}, S_{g0}, N_{g0}\}_{g=1}^{G}$. For the stock of fatalities, recovered and vaccinated, this value is zero, that is, $F_{g0} = C_{g0} = V_{g0} = 0$. Knowing the number of fatalities in the next two periods, we then obtain I_{g0} and R_{g0} from (53) and (51); and the number of susceptible is directly obtained from (1) taking $N_{gt} = N_{g0}$ for all t from the sources reported in Table 5.

In principle, knowing those numbers, and taking the daily deaths and fraction of vaccinated $\{f_{gt}, \lambda_{gt}\}_{g=1,t=1}^{G,\mathfrak{T}}$ from the data, we could end up with a system of four *times* G equations, given by (56) to (58), and four *times* G unknowns, $\{\rho_{gt}, S_{gt+1}, C_{gt+1}, V_{gt+1}\}_{g=1}^{G}$ that is solvable. However, the large number of zero deaths encountered in many periods make the system indeterminate many times when the geographical component is considered. The solution that we have adopted to solve this problem is assuming in the calibration of ρ_g that $\kappa = 0$. In this way, the system for each region simplifies and becomes independent of other areas. Hence, for each period $t \in [1, \mathfrak{T}]$ and region $g \in [1, G]$, we first recover ρ_{gt} from (56) and then $\{S_{gt+1}, C_{gt+1}, V_{gt+1}\}_{g=1}^{G}$ from the other three equations.

C Figures and Tables

Figure 1: Total daily deaths in the EU27 and the UK

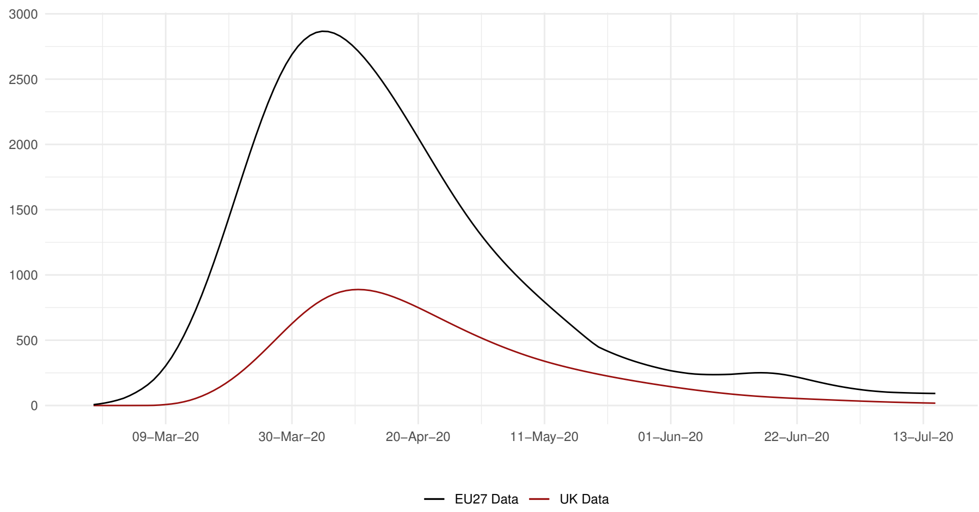

Figure 2: Daily deaths per 100,000 inhabitants in the EU27 and the UK

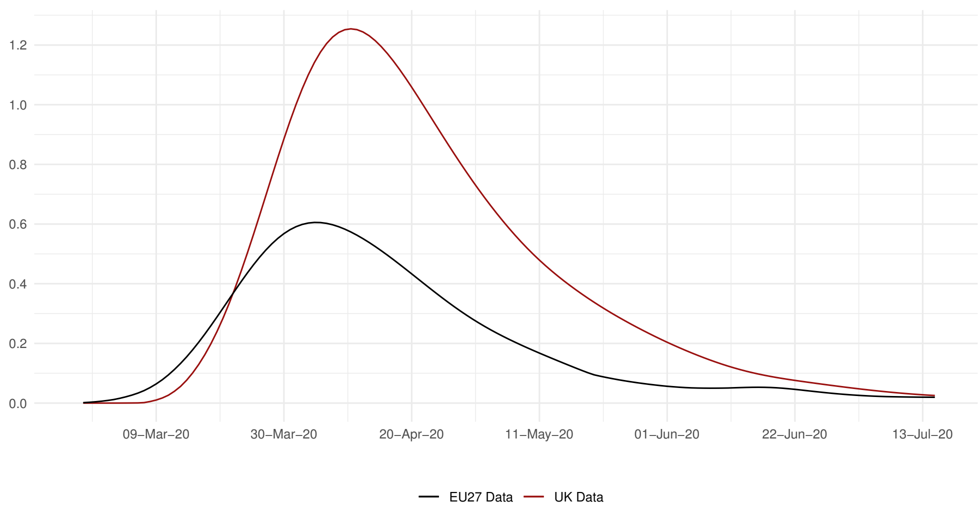

Figure 3: Average daily ρ_g in the EU27 and the UK

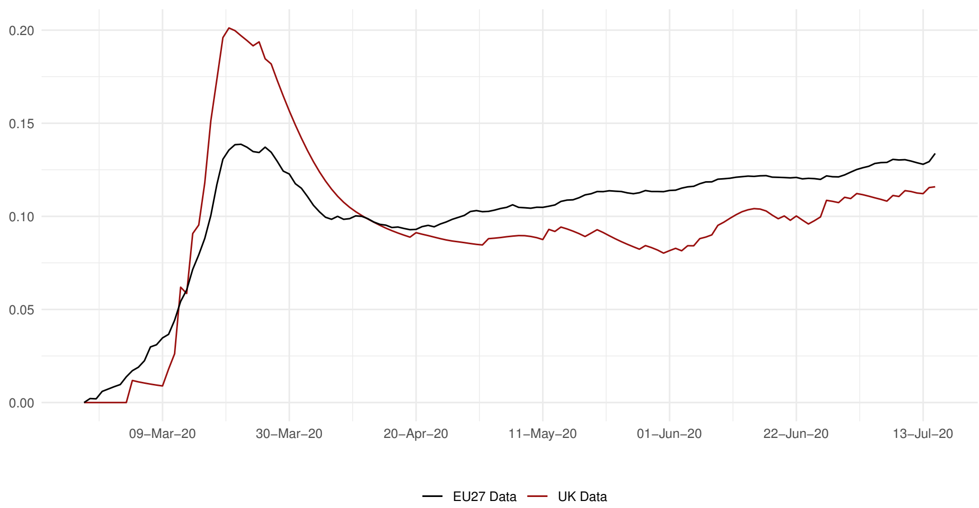

Figure 4: Total daily deaths in the UK NUTS2 regions

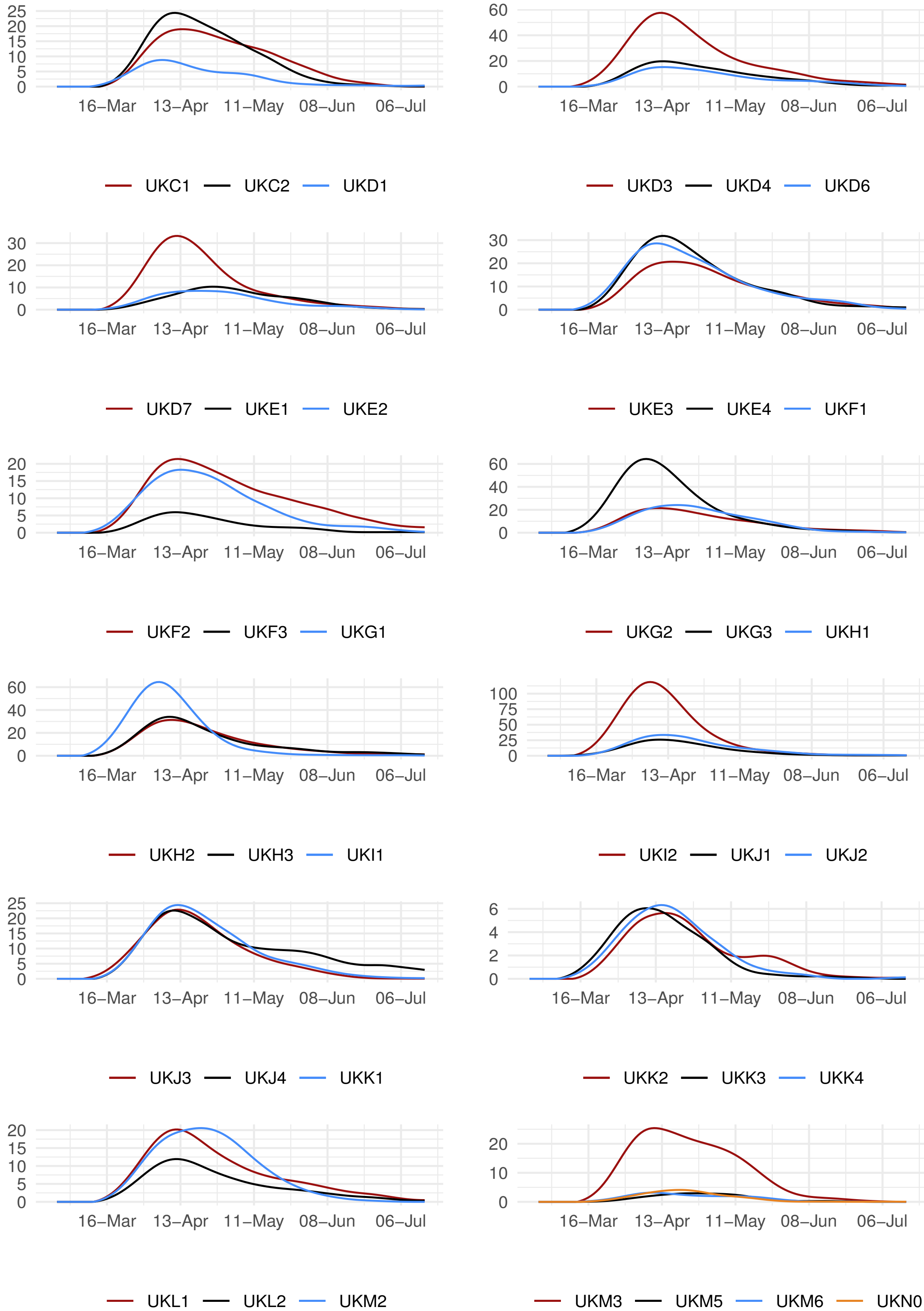

Figure 5: Daily deaths: data versus predictions

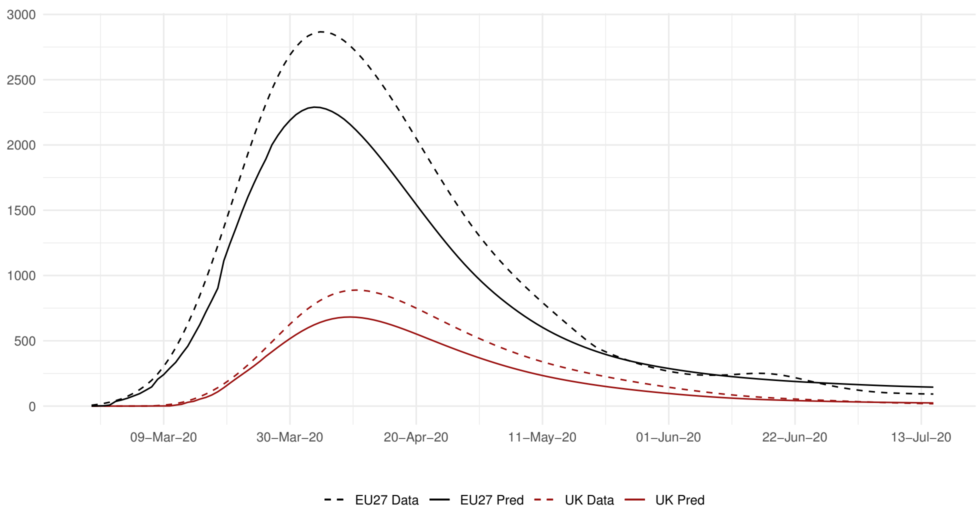

Table 1: NUTS2 Regions

Code	Region	Code	Region
AT11	Burgenland (AT)	BE1	Région Bruxelles-Capitale / Brussels H G
AT12	Niederösterreich	BE2	Vlaams Gewest
AT13	Wien	BE3	Région wallonne
AT21	Kärnten	BG	Bulgaria
AT22	Steiermark	CYP	Kypros
AT31	Oberösterreich	CZ01	Praha
AT32	Salzburg	CZ02	Strední Cechy
AT33	Tirol	CZ03	Jihozápad
AT34	Vorarlberg	CZ04	Severozápad
DE11	Stuttgart	CZ05	Severovýchod
DE12	Karlsruhe	CZ06	Jihovýchod
DE13	Freiburg	CZ07	Strední Morava
DE14	Tübingen	CZ08	Moravskoslezsko
DE21	Oberbayern	DE30	Berlin
DE22	Niederbayern	DE40	Brandenburg
DE23	Oberpfalz	DE50	Bremen
DE24	Oberfranken	DE60	Hamburg
DE25	Mittelfranken	DE71	Darmstadt
DE26	Unterfranken	DE72	Gießen
DE27	Schwaben	DE73	Kassel
DE80	Mecklenburg-Vorpommern	DEA1	Düsseldorf
DE91	Braunschweig	DEA2	Köln
DE92	Hannover	DEA3	Münster
DE93	Lüneburg	DEA4	Detmold
DE94	Weser-Ems	DEA5	Arnsberg
DED2	Dresden	DEE0	Sachsen-Anhalt
DED4	Chemnitz	DEF0	Schleswig-Holstein
DED5	Leipzig	DEG0	Thüringen
DK01	Hovedstaden	DK02	Sjælland
DK03	Syddanmark	DK04	Midtjylland
DK05	Nordjylland	EE00	Eesti
EL11	Anatoliki Makedonia, Thraki	EL12	Kentriki Makedonia
EL13	Dytiki Makedonia	EL14	Thessalia
EL21	Ipeiros	EL22	Ionia Nisia
EL23	Dytiki Ellada	EL24	Sterea Ellada
EL25	Peloponnisos	EL30	Attiki
EL41	Voreio Aigaio	EL42	Notio Aigaio

Table 1: NUTS2 Regions

Code	Region	Code	Region
EL43	Kriti	ES11	Galicia
ES12	Principado de Asturias	ES13	Cantabria
ES21	País Vasco	ES22	Comunidad Foral de Navarra
ES23	La Rioja	ES24	Aragón
ES30	Comunidad de Madrid	ES41	Castilla y León
ES42	Castilla-la Mancha	ES43	Extremadura
ES51	Cataluña	ES52	Comunidad Valenciana
ES53	Illes Balears	ES61	Andalucía
ES62	Región de Murcia	ES63	Ciudad Autónoma de Ceuta (ES)
ES64	Ciudad Autónoma de Melilla (ES)	ES70	Canarias (ES)
FI19	Länsi-Suomi	FI1B	Helsinki-Uusimaa
FI1C	Etelä-Suomi	FI1D	Pohjois- ja Itä-Suomi
FI20	Åland	FR10	Île de France
FR21	Champagne-Ardenne	FR22	Picardie
FR23	Haute-Normandie	FR24	Centre (FR)
FR25	Basse-Normandie	FR26	Bourgogne
FR30	Nord - Pas-de-Calais	FR41	Lorraine
FR42	Alsace	FR43	Franche-Comté
FR51	Pays de la Loire	FR52	Bretagne
FR53	Poitou-Charentes	FR61	Aquitaine
FR62	Midi-Pyrénées	FR63	Limousin
FR71	Rhône-Alpes	FR72	Auvergne
FR81	Languedoc-Roussillon	FR82	Provence-Alpes-Côte d'Azur
FR83	Corse	HRV	Croatia
HU	Hungary	IE	Ireland
ITC1	Piemonte	ITC2	Valle d'Aosta/Vallée d'Aoste
ITC3	Liguria	ITC4	Lombardia
ITF1	Abruzzo	ITF2	Molise
ITF3	Campania	ITF4	Puglia
ITF5	Basilicata	ITF6	Calabria
ITG1	Sicilia	ITG2	Sardegna
ITH1	Provincia Autonoma di Bolzano/Bozen	ITH2	Provincia Autonoma di Trento
ITH3	Veneto	ITH4	Friuli-Venezia Giulia
ITH5	Emilia-Romagna	ITI1	Toscana
ITI2	Umbria	ITI3	Marche
ITI4	Lazio	LTU	Lietuva
LUX	Luxembourg	LVA	Latvija
MLT	Malta	NL	Netherlands

Table 1: NUTS2 Regions

Code	Region	Code	Region
PL11	Lódzkie	PL12	Mazowieckie
PL21	Malopolskie	PL22	Slaskie
PL31	Lubelskie	PL32	Podkarpackie
PL33	Swietokrzyskie	PL34	Podlaskie
PL41	Wielkopolskie	PL42	Zachodniopomorskie
PL43	Lubuskie	PL51	Dolnoslaskie
PL52	Opolskie	PL61	Kujawsko-Pomorskie
PL62	Warminsko-Mazurskie	PL63	Pomorskie
PT11	Norte	PT15	Algarve
PT16	Centro (PT)	PT17	Área Metropolitana de Lisboa
PT18	Alentejo	PT20	Região Autónoma dos Açores (PT)
PT30	Região Autónoma da Madeira (PT)	RO	Romania
ROW	Rest of the world	SE11	Stockholm
SE12	Östra Mellansverige	SE21	Småland med öarna
SE22	Sydsverige	SE23	Västsverige
SE31	Norra Mellansverige	SE32	Mellersta Norrland
SE33	Övre Norrland	SI01	Vzhodna Slovenija
SI02	Zahodna Slovenija	SK01	Bratislavský kraj
SK02	Západné Slovensko	SK03	Stredné Slovensko
SK04	Východné Slovensko	UKC1	Tees Valley and Durham
UKC2	Northumberland and Tyne and Wear	UKD1	Cumbria
UKD3	Greater Manchester	UKD4	Lancashire
UKD6	Cheshire	UKD7	Merseyside
UKE1	East Yorkshire and Northern Lincolnshire	UKE2	North Yorkshire
UKE3	South Yorkshire	UKE4	West Yorkshire
UKF1	Derbyshire and Nottinghamshire	UKF2	Leicestershire, Rutland and Northamptonshire
UKF3	Lincolnshire	UKG1	Herefordshire, Worcestershire and Warwickshire
UKG2	Shropshire and Staffordshire	UKG3	West Midlands
UKH1	East Anglia	UKH2	Bedfordshire and Hertfordshire
UKH3	Essex	UKI1	Inner London - West
UKI2	Inner London - East	UKJ1	Berkshire, Buckinghamshire and Oxfordshire
UKJ2	Surrey, East and West Sussex	UKJ3	Hampshire and Isle of Wight
UKJ4	Kent	UKK1	Gloucestershire, Wiltshire and Bristol/Bath area
UKK2	Dorset and Somerset	UKK3	Cornwall and Isles of Scilly

Table 1: NUTS2 Regions

Code	Region	Code	Region
UKK4	Devon	UKL1	West Wales and The Valleys
UKL2	East Wales	UKM2	Eastern Scotland
UKM3	South Western Scotland	UKM5	North Eastern Scotland
UKM6	Highlands and Islands	UKN0	Northern Ireland (UK)

Table 2: NACE Rev2 sectors included in the analysis

Section	Industry
A	Agriculture, forestry and fishing
B_E	Industry (except construction and mining)
C	Mining
F	Construction
G_I	Wholesale and retail trade, transport, accommodation and food service activities
J	Information and communication
K_L	Financial, insurance, and real estate activities
M_N	Professional, scientific, technical, administrative and support service activities
O_Q	Public administration, defence, education, human health and social work activities
R_U	Arts, entertainment and recreation; other service activities; activities of household and extra-territorial organizations and bodies

Table 3: Calibration Summary

Parameter	Source	Value | Description
α_g^j	Thissen et al. (2019)	Share of sector j in total consumption expenditure in location g
γ_g^j	Thissen et al. (2019)	Share of value added in gross output
γ_g^{kj}	Thissen et al. (2019)	Input-output coefficients
θ^j, Θ^j	Thissen et al. (2019) and Persyn et al. (2020)	Gravity equation estimation
Λ_g	Dingel and Neiman (2020)	Estimated using data on who can work from home and trade shares
κ	Eichenbaum et al. (2020)	0.17 | Average infection rate related to work
ϕ	Fernández-Villaverde and Jones (2020)	0.125 | Average infections per period. Then $1/\phi = 8$ days
ξ	Fernández-Villaverde and Jones (2020)	0.143 | Average number of days to resolve. Then, $1/\xi = 7$ days
δ	Fernández-Villaverde and Jones (2020)	0.01 | Average fatality rate
λ_g	Direct data on vaccinations	Estimated by regions
α^V	Several sources	0.159 | Evidence on vaccine effectiveness
α^C	Several sources	0.168 | Evidence on reinfection rates
ρ_g	Fernández-Villaverde and Jones (2020)	Time varying infection rate calibrated as a residual using the model

Table 4: Sector-specific shape parameters of the Fréchet distributions

Sectors	Intermediates	Finals
A	2.7776	2.7754
B_E	2.8126	2.8036
C	1.9930	1.9428
F	3.0822	3.0822
G_I	2.7182	2.7420
J	2.7242	2.6601
K_L	2.9438	2.9439
M_N	2.8146	2.8298
O_Q	3.0900	3.0903
R_U	3.0257	3.0228

Table 5: Death and infection data sources by country

Country	Country code	Number of regions	Indicator*	Source
Austria	AT	9	Deaths, population	AGES
Belgium	BE	3	Deaths	Sciensano
Bulgaria	BG	1	Deaths	Our World In Data
Croatia	HR	1	Deaths	Our World In Data
Cyprus	CY	1	Deaths	Our World In Data
Czech Republic	CZ	8	Deaths	Ministry of Health
Denmark	DK	5	Infections	Statens Serum Institut
Estonia	EE	1	Deaths	Our World In Data
Finland	FI	5	Deaths	Helsing Sanomat
France	FR	22	Deaths	Government Statistical Office
Germany	DE	38	Deaths	Robert Koch Institute
Greece	EL	13	Infections	Ministry of Health
Hungary	HU	1	Deaths	Our World In Data
Ireland	IE	1	Deaths	Our World In Data
Italy	IT	21	Deaths	Dipartimento della Protezion Civile
Latvia	LV	1	Deaths	Our World In Data
Lithuania	LT	1	Deaths	Our World In Data
Luxembourg	LU	1	Deaths	Our World In Data
Malta	MT	1	Deaths	Our World In Data
Netherlands	NL	1	Deaths	Our World In Data
Poland	PL	16	Deaths	Government of Poland
Portugal	PT	7	Deaths	Ministry of Health
Rest of the World	ROW	1	Infections	Our World In Data
Romania	RO	2	Deaths	Our World In Data
Slovakia	SK	4	Infections	Radovan Ondas**
Slovenia	SI	2	Deaths	COVID-19 Sledilnik
Spain	ES	19	Deaths	Narrativa Tracking
Sweden	SE	8	Deaths	Public Health Agency of Sweden
United Kingdom	UK	37	Infections	National Health Service

* Population numbers at the time when the pandemic started come from the same sources.

** Radovan Ondas independently compiled a machine readable dataset from the reports published by the National Health Information Centre. The data is accessible in his GitHub Repository: https://github.com/radoondas/covid-19-slovakia/

Table 6: Values for certain economic variables in the initial period

Region	Employment (,000)	Wages (,000)	Tax per capita	Region	Employment (,000)	Wages (,000)	Tax per capita
AT11	134.0	26.582	-7.263	FR61	1351.6	36.943	-1.070
AT12	782.3	30.316	-12.218	FR62	1243.7	38.053	-5.194
AT13	796.1	51.764	-15.269	FR63	295.9	32.894	0.362
AT21	257.5	33.961	-11.470	FR71	2699.9	41.459	-6.766
AT22	584.6	34.507	-10.782	FR72	537.3	35.294	-0.426
AT31	719.2	37.197	-17.733	FR81	955.4	36.560	-12.551
AT32	273.8	39.259	-22.797	FR82	1955.2	40.466	-2.172
AT33	369.8	34.640	-20.136	FR83	62.2	76.115	5.869
AT34	187.4	36.073	-23.458	HRV	1524.0	13.286	-4.580
BE10	412.6	96.775	-15.889	HU00	3892.8	11.470	-4.055
BE20	2774.6	41.152	-15.051	IE00	1888.5	37.022	-12.201
BE30	1343.2	36.687	-2.747	ITC1	1770.7	28.079	2.619
BG00	2934.9	5.662	-3.473	ITC2	54.7	29.565	1.156
CYP	365.1	22.851	-10.685	ITC3	603.1	28.411	2.506
CZ01	649.4	27.075	-22.304	ITC4	4221.5	32.745	3.376
CZ02	626.2	10.431	-4.104	ITF1	485.9	24.778	0.550
CZ03	576.1	11.787	-4.412	ITF2	98.6	23.228	-1.146
CZ04	504.8	10.136	-3.759	ITF3	1580.5	25.247	1.002
CZ05	689.5	11.280	-2.701	ITF4	1158.4	25.028	-1.909
CZ06	792.9	12.658	-5.787	ITF5	178.6	23.431	-1.743
CZ07	554.2	11.232	-2.121	ITF6	518.2	24.357	-5.995
CZ08	544.1	12.379	-4.676	ITG1	1334.7	26.096	-0.919
DE11	2024.8	46.418	-19.429	ITG2	546.3	24.201	-1.089
DE12	1382.3	40.482	-7.598	ITH1	243.0	34.195	-149.067
DE13	1141.4	33.852	0.691	ITH2	229.2	31.358	-133.874
DE14	943.3	37.081	1.375	ITH3	2043.1	27.872	-21.282
DE21	2376.5	44.906	-30.306	ITH4	495.5	30.221	-64.095
DE22	626.0	31.706	3.137	ITH5	1904.1	29.684	-19.811
DE23	566.2	34.709	4.314	ITI1	1534.1	26.074	-22.678
DE24	542.5	33.663	6.094	ITI2	349.0	24.186	-80.430
DE25	864.6	41.955	3.737	ITI3	615.7	24.433	-62.624
DE26	674.6	34.375	3.437	ITI4	2225.5	33.170	-6.193
DE27	919.4	34.923	0.761	LTU	1292.8	10.625	-3.610
DE30	1604.1	36.535	-9.281	LUX	238.7	94.932	-29.984
DE40	1200.1	24.884	-19.873	LVA	893.9	10.539	-9.128

Table 6: Values for certain economic variables in the initial period

Region	Employment (,000)	Wages (,000)	Tax per capita	Region	Employment (,000)	Wages (,000)	Tax per capita
DE50	299.1	51.296	2.623	MLT	181.6	18.957	-21.888
DE60	885.6	54.994	-18.539	NL00	8285.3	39.156	-15.015
DE71	1912.2	45.963	-37.108	PL11	1247.7	6.867	-1.807
DE72	503.5	33.955	5.715	PL12	1044.0	6.136	-10.795
DE73	591.4	37.559	4.617	PL21	1314.9	8.955	-3.773
DE80	741.9	26.457	1.978	PL22	1903.3	10.471	-6.689
DE91	734.0	40.740	2.966	PL31	957.8	5.988	-0.758
DE92	1013.5	35.950	-0.458	PL32	800.1	7.504	-0.548
DE93	804.8	24.695	2.341	PL33	554.0	6.192	-1.144
DE94	1214.6	30.523	-5.334	PL34	453.3	7.127	-0.924
DEA1	2364.0	40.903	-31.247	PL41	1365.6	9.896	-6.177
DEA2	2013.5	40.181	-29.272	PL42	572.4	9.223	-3.354
DEA3	1209.3	32.514	-4.406	PL43	404.7	7.845	-2.437
DEA4	968.6	35.664	0.693	PL51	1055.6	11.646	-6.788
DEA5	1623.0	36.641	-3.571	PL52	346.1	9.092	-3.167
DEB1	717.0	30.416	2.206	PL61	761.4	8.427	-2.292
DEB2	264.5	27.323	5.418	PL62	528.7	7.500	-1.866
DEB3	981.0	34.487	-1.896	PL63	894.1	9.448	-4.990
DEC0	464.8	37.471	-16.756	PT11	1543.9	14.458	-5.570
DED2	743.8	29.692	-2.809	PT15	186.9	14.699	-9.925
DED4	688.1	26.945	-1.295	PT16	1059.2	12.866	-5.925
DED5	474.6	30.726	-11.489	PT17	1132.9	26.130	-10.925
DEE0	1048.9	26.492	-0.673	PT18	298.5	14.760	-5.861
DEF0	1336.9	29.431	-1.028	PT20	99.2	16.322	-6.223
DEG0	1067.1	26.589	0.795	PT30	108.8	16.377	-17.914
DK01	858.4	61.770	-17.926	RO00	8549.1	5.349	-4.747
DK02	367.7	37.375	-10.079	ROW	942281.9	6.379	-21.974
DK03	538.9	47.297	-21.957	SE11	1133.4	57.620	-32.283
DK04	606.0	46.647	-19.716	SE12	750.4	43.493	-10.368
DK05	265.2	45.533	-22.082	SE21	394.9	42.934	-16.470
EE00	621.3	13.873	-8.711	SE22	672.4	43.034	-14.361
EL11	187.4	13.975	-1.287	SE23	951.4	45.211	-19.223
EL12	553.6	15.569	-2.522	SE31	387.3	40.281	-14.935
EL13	77.1	22.555	-10.095	SE32	172.5	41.157	-18.188
EL14	235.5	13.886	-2.724	SE33	242.2	44.075	-19.639

Table 6: Values for certain economic variables in the initial period

Region	Employment (,000)	Wages (,000)	Tax per capita	Region	Employment (,000)	Wages (,000)	Tax per capita
EL21	103.9	13.513	-1.575	SI01	473.5	16.270	-6.015
EL22	75.2	13.777	-6.052	SI02	432.4	23.982	-8.198
EL23	202.7	13.852	-3.918	SK01	315.2	25.285	-37.207
EL24	171.3	15.648	-7.450	SK02	824.8	9.903	-4.622
EL25	191.3	13.472	-3.304	SK03	563.9	10.025	-3.793
EL30	1312.0	22.400	-11.083	SK04	625.4	8.968	-2.845
EL41	65.6	14.652	-1.155	UKC1	491.7	17.574	-3.107
EL42	122.8	17.225	-7.810	UKC2	641.4	18.338	-4.316
EL43	214.8	14.179	-5.425	UKD1	240.1	17.303	-5.735
ES11	1006.4	23.089	-9.808	UKD3	1215.3	20.438	-5.678
ES12	369.4	25.605	-8.770	UKD4	639.2	18.059	-5.299
ES13	222.5	23.698	-7.971	UKD6	431.8	20.000	-482.572
ES21	873.6	33.219	-10.681	UKD7	657.2	18.000	-192.049
ES22	258.1	30.630	-11.029	UKE1	422.9	17.903	-5.425
ES23	124.5	24.648	-13.305	UKE2	386.9	17.838	-6.861
ES24	515.3	27.559	-11.060	UKE3	621.8	16.243	-4.002
ES30	2718.1	35.590	-12.687	UKE4	1006.7	20.347	-5.931
ES41	916.4	24.179	-7.936	UKF1	973.3	18.111	-4.702
ES42	712.3	21.324	-8.212	UKF2	816.7	20.108	-5.229
ES43	339.7	21.775	-4.217	UKF3	342.8	13.848	-6.070
ES51	2969.6	29.935	-11.567	UKG1	642.1	18.541	-7.249
ES52	1771.2	23.223	-8.090	UKG2	754.6	15.956	-5.027
ES53	475.8	23.426	-10.654	UKG3	1136.4	20.761	-5.159
ES61	2571.5	23.665	-6.053	UKH1	1155.3	19.056	-6.970
ES62	514.9	23.302	-12.779	UKH2	885.8	23.202	-5.794
ES63	25.6	33.891	-0.382	UKH3	839.2	16.779	-4.313
ES64	24.6	31.541	0.014	UKI1	1524.1	63.399	-51.863
ES70	729.7	24.064	-7.055	UKI2	2238.5	19.722	-4.353
FI19	600.6	38.136	-73.287	UKJ1	1184.5	30.080	-10.911
FI1B	796.1	48.499	1.898	UKJ2	1360.9	20.605	-5.798
FI1C	502.2	37.192	3.059	UKJ3	938.1	21.087	-5.775
FI1D	542.9	36.367	1.162	UKJ4	806.6	16.680	-4.745
FI20	15.0	47.661	6.337	UKK1	1171.8	20.758	-7.030
FR10	5277.6	64.750	-17.352	UKK2	615.3	15.670	-4.123
FR21	506.9	37.200	-5.522	UKK3	238.8	13.092	-3.574

Table 6: Values for certain economic variables in the initial period

Region	Employment (,000)	Wages (,000)	Tax per capita	Region	Employment (,000)	Wages (,000)	Tax per capita
FR22	728.0	34.172	-1.195	UKK4	512.6	16.107	-4.338
FR23	717.5	39.026	-0.711	UKL1	851.5	13.342	-3.091
FR24	1000.7	36.918	-5.498	UKL2	535.7	18.690	-6.418
FR25	578.5	35.348	0.511	UKM2	962.8	18.727	-3.527
FR26	639.7	36.367	-0.802	UKM3	991.2	19.921	-2.492
FR30	1492.6	40.037	-9.713	UKM5	251.7	39.198	-22.072
FR41	904.6	33.876	-3.644	UKM6	233.6	14.205	-7.639
FR42	809.4	38.182	-1.524	UKN0	797.2	15.945	-3.035
FR43	468.6	34.315	-1.568				
FR51	1509.7	38.074	-5.185				
FR52	1336.1	35.452	-6.330				
FR53	714.1	33.652	-2.779				

Table 7: Values for certain disease-related variables in the initial period

Region	Start of the pandemic	Non-telematic workers (%)	Infected	Region	Start of the pandemic	Non-telematic workers (%)	Infected
AT11	27-Mar	0.643	103.044	FR61	22-Mar	0.652	4015.271
AT12	19-Mar	0.636	1949.035	FR62	19-Mar	0.637	1854.444
AT13	14-Mar	0.593	1852.674	FR63	22-Mar	0.658	927.643
AT21	30-Mar	0.634	411.027	FR71	18-Mar	0.641	20220.949
AT22	17-Mar	0.645	2239.692	FR72	26-Mar	0.649	1584.200
AT31	23-Mar	0.646	1532.013	FR81	18-Mar	0.681	4746.184
AT32	26-Mar	0.619	1097.628	FR82	19-Mar	0.639	8072.069
AT33	21-Mar	0.619	2603.076	FR83	19-Mar	0.651	1388.133
AT34	29-Mar	0.640	616.282	HRV	27-Mar	0.628	1139.221
BE10	10-Mar	0.606	4803.839	HU00	20-Mar	0.659	1439.566
BE20	14-Mar	0.650	25756.309	IE00	21-Mar	0.611	7687.612
BE30	15-Mar	0.658	23732.681	ITC1	05-Mar	0.653	10748.732
BG00	27-Mar	0.646	1336.648	ITC2	17-Mar	0.657	3390.699
CYP	29-Mar	0.606	327.516	ITC3	04-Mar	0.652	5371.631
CZ01	24-Mar	0.590	2612.614	ITC4	20-Feb	0.650	65345.453
CZ02	30-Mar	0.666	832.420	ITF1	14-Mar	0.658	4934.933
CZ03	06-Apr	0.668	630.218	ITF2	19-Mar	0.661	464.173
CZ04	30-Mar	0.660	912.995	ITF3	13-Mar	0.659	5534.914
CZ05	01-Apr	0.672	425.525	ITF4	07-Mar	0.667	1735.225
CZ06	01-Apr	0.662	734.146	ITF5	26-Mar	0.668	858.063
CZ07	30-Mar	0.666	438.712	ITF6	18-Mar	0.679	2213.232
CZ08	30-Mar	0.662	603.674	ITG1	16-Mar	0.665	4125.970
DE11	06-Mar	0.667	3280.369	ITG2	20-Mar	0.665	2285.404
DE12	12-Mar	0.658	2525.148	ITH1	13-Mar	0.635	3647.874
DE13	08-Mar	0.667	3829.431	ITH2	14-Mar	0.635	6967.356
DE14	15-Mar	0.668	5409.605	ITH3	02-Mar	0.640	4053.239
DE21	13-Mar	0.645	10327.778	ITH4	09-Mar	0.636	3351.826
DE22	16-Mar	0.665	5266.321	ITH5	28-Feb	0.641	12422.694
DE23	15-Mar	0.662	6770.607	ITI1	11-Mar	0.639	8172.510
DE24	15-Mar	0.662	3235.555	ITI2	19-Mar	0.637	2022.638
DE25	19-Mar	0.653	6599.939	ITI3	03-Mar	0.636	5089.702
DE26	11-Mar	0.660	2449.937	ITI4	07-Mar	0.639	3240.823
DE27	13-Mar	0.663	2273.360	LTU	25-Mar	0.681	568.314
DE30	17-Mar	0.620	6112.987	LUX	18-Mar	0.598	1508.562
DE40	24-Mar	0.639	4756.678	LVA	11-Apr	0.649	499.430
DE50	25-Mar	0.642	1018.454	MLT	10-Apr	0.599	98.637
DE60	12-Mar	0.626	2122.158	NL00	09-Mar	0.636	15453.226
DE71	19-Mar	0.626	5456.108	PL11	02-Apr	0.663	466.260
DE72	23-Mar	0.662	1030.016	PL12	25-Mar	0.611	2133.254
DE73	22-Mar	0.661	3268.592	PL21	01-Apr	0.652	730.002
DE80	26-Mar	0.653	847.376	PL22	28-Mar	0.657	2415.361
DE91	17-Mar	0.659	3850.167	PL31	29-Mar	0.673	369.333
DE92	19-Mar	0.656	3142.748	PL32	01-Apr	0.671	629.576

Table 7: Values for certain disease-related variables in the initial period

Region	Start of the pandemic	Non-telematic workers (%)	Infected	Region	Start of the pandemic	Non-telematic workers (%)	Infected
DE93	25-Mar	0.660	1810.941	PL33	15-Apr	0.669	287.577
DE94	14-Mar	0.665	2100.665	PL34	15-Apr	0.675	74.174
DEA1	11-Mar	0.637	3617.624	PL41	31-Mar	0.669	2145.465
DEA2	06-Mar	0.610	4521.161	PL42	18-Apr	0.666	546.586
DEA3	17-Mar	0.660	4106.123	PL43	22-Jul	0.672	497.269
DEA4	17-Mar	0.664	1619.907	PL51	24-Mar	0.659	648.968
DEA5	18-Mar	0.668	4113.175	PL52	06-Apr	0.672	781.619
DEB1	16-Mar	0.659	1420.570	PL61	07-Apr	0.669	979.346
DEB2	25-Mar	0.657	586.702	PL62	10-Aug	0.677	232.002
DEB3	20-Mar	0.665	2279.947	PL63	21-Apr	0.656	1012.212
DEC0	17-Mar	0.635	2913.969	PT11	20-Mar	0.646	7663.833
DED2	19-Mar	0.634	1516.737	PT15	01-Apr	0.641	402.946
DED4	21-Mar	0.641	3703.584	PT16	20-Mar	0.656	3630.319
DED5	26-Mar	0.623	669.239	PT17	20-Mar	0.603	2762.330
DEE0	20-Mar	0.662	1689.044	PT18	24-Jun	0.666	788.249
DEF0	16-Mar	0.656	2470.665	PT20	10-Apr	0.667	377.163
DEG0	21-Mar	0.661	2215.732	PT30	13-Oct	0.652	0.001
DK01	28-Feb	0.599	5.233	RO00	21-Mar	0.651	8706.891
DK02	03-Mar	0.649	4.319	ROW	25-Feb	0.635	339.840
DK03	01-Mar	0.651	3.753	SE11	26-Mar	0.580	25240.461
DK04	15-Jul	0.654	0.867	SE12	26-Mar	0.623	7369.381
DK05	08-Mar	0.659	3.542	SE21	26-Mar	0.635	1349.541
EE00	30-Mar	0.652	1611.450	SE22	26-Mar	0.615	1041.884
EL11	12-Oct	0.632	3.748	SE23	26-Mar	0.616	2741.393
EL12	15-Jul	0.630	3.283	SE31	26-Mar	0.629	2819.716
EL13	10-Aug	0.635	3.339	SE32	07-Apr	0.614	1370.495
EL14	29-Jul	0.637	3.819	SE33	05-Apr	0.623	1578.364
EL21	28-Aug	0.630	3.100	SI01	23-Mar	0.670	1414.387
EL22	09-Nov	0.588	3.039	SI02	28-Mar	0.643	983.944
EL23	15-Aug	0.630	3.074	SK01	18-Aug	0.614	22.267
EL24	08-Sep	0.643	3.163	SK02	15-Mar	0.665	3.454
EL25	09-Aug	0.630	3.274	SK03	25-Aug	0.667	9.379
EL30	09-Nov	0.607	10.546	SK04	10-Aug	0.669	9.062
EL41	14-Aug	0.598	3.531	UKC1	15-Mar	0.627	4.767
EL42	11-Oct	0.554	3.442	UKC2	13-Mar	0.624	5.420
EL43	09-Aug	0.580	3.797	UKD1	09-Mar	0.631	4.039
ES11	15-Mar	0.640	4876.296	UKD3	09-Mar	0.620	5.866
ES12	18-Mar	0.632	4225.524	UKD4	13-Mar	0.631	5.712
ES13	20-Mar	0.635	3846.428	UKD6	15-Mar	0.592	5.117
ES21	07-Mar	0.635	5876.978	UKD7	12-Mar	0.598	5.689
ES22	16-Mar	0.644	6582.146	UKE1	18-Mar	0.635	4.117
ES23	11-Mar	0.648	2601.451	UKE2	15-Mar	0.626	4.362
ES24	07-Mar	0.639	1332.486	UKE3	08-Mar	0.627	5.025

Table 7: Values for certain disease-related variables in the initial period

Region	Start of the pandemic	Non-telematic workers (%)	Infected	Region	Start of the pandemic	Non-telematic workers (%)	Infected
ES30	07-Mar	0.587	73177.142	UKE4	12-Mar	0.622	5.105
ES41	13-Mar	0.642	21223.621	UKF1	06-Mar	0.631	4.893
ES42	11-Mar	0.637	20920.870	UKF2	10-Mar	0.627	5.393
ES43	15-Mar	0.645	7275.205	UKF3	16-Mar	0.639	4.339
ES51	09-Mar	0.625	22908.766	UKG1	09-Mar	0.631	4.532
ES52	12-Mar	0.633	13245.641	UKG2	10-Mar	0.631	4.823
ES53	19-Mar	0.583	3553.364	UKG3	06-Mar	0.623	6.405
ES61	13-Mar	0.630	11181.436	UKH1	10-Mar	0.628	4.955
ES62	22-Mar	0.649	3989.206	UKH2	08-Mar	0.622	4.615
ES63	04-Apr	0.637	107.564	UKH3	10-Mar	0.627	5.537
ES64	03-Sep	0.639	73.033	UKI1	01-Mar	0.593	6.144
ES70	16-Mar	0.590	3136.775	UKI2	04-Mar	0.612	12.268
FI19	05-Mar	0.620	5986.344	UKJ1	05-Mar	0.612	5.290
FI1B	26-Feb	0.653	5548.468	UKJ2	07-Mar	0.617	5.405
FI1C	06-Mar	0.666	3868.857	UKJ3	06-Mar	0.617	4.509
FI1D	03-Mar	0.669	3197.378	UKJ4	11-Mar	0.627	5.676
FI20	21-Mar	0.661	334.259	UKK1	09-Mar	0.621	4.940
FR10	18-Mar	0.630	84443.478	UKK2	17-Mar	0.630	3.947
FR21	19-Mar	0.660	5846.306	UKK3	14-Mar	0.630	3.853
FR22	18-Mar	0.659	12914.460	UKK4	11-Mar	0.628	3.426
FR23	19-Mar	0.656	3153.497	UKL1	10-Mar	0.630	6.153
FR24	22-Mar	0.651	7177.193	UKL2	09-Mar	0.628	6.211
FR25	23-Mar	0.653	2811.046	UKM2	09-Mar	0.624	4.763
FR26	18-Mar	0.656	6448.034	UKM3	08-Mar	0.625	5.131
FR30	18-Mar	0.648	7110.021	UKM5	19-Jul	0.614	1.513
FR41	18-Mar	0.656	24535.396	UKM6	13-Mar	0.634	3.505
FR42	18-Mar	0.650	34338.163	UKN0	15-Mar	0.630	4.439
FR43	18-Mar	0.658	7869.257				
FR51	21-Mar	0.650	6747.541				
FR52	18-Mar	0.645	3074.450				
FR53	21-Mar	0.657	2696.476				

Table 8: Results

Region code	Region name	Total	per 100,000	Total	Geographic (%)	Total	Increase (%)	Lives saved*
EU27	European Union	133063	28	107112	10.2	4545222	4143	202
UK	United Kingdom	40672	57	30571	9.7	1248078	3983	1718
UKC1	Tees Valley and Durham	1037	87	737	9.9	19622	2564	1581
UKC2	Northumberland and Tyne and Wear	1095	76	827	12.8	22484	2619	1497
UKD1	Cumbria	382	77	323	8.6	6302	1854	1199
UKD3	Greater Manchester	2587	93	1660	9.8	63906	3749	2231
UKD4	Lancashire	1016	68	762	9.4	22772	2889	1480
UKD6	Cheshire	829	90	505	9.1	21494	4158	2271
UKD7	Merseyside	1283	83	920	10.1	29038	3057	1824
UKE1	East Yorkshire and Northern Lincolnshire	546	59	409	11.7	10115	2374	1045
UKE2	North Yorkshire	464	57	353	11.5	13982	3865	1666
UKE3	South Yorkshire	1120	81	788	8.7	24589	3021	1713
UKE4	West Yorkshire	1440	63	1052	11.2	46595	4330	1979
UKF1	Derbyshire and Nottinghamshire	1416	65	977	10.6	49536	4970	2220
UKF2	Leicestershire, Rutland and Northamptonshire	1250	69	863	8.6	35603	4026	1916
UKF3	Lincolnshire	262	35	237	10.5	6585	2680	849
UKG1	Herefordshire, Worcestershire and Warwickshire	942	70	651	11.6	25729	3852	1874
UKG2	Shropshire and Staffordshire	1121	69	815	9.4	29821	3560	1797
UKG3	West Midlands	2496	87	1737	13.4	63443	3553	2140
UKH1	East Anglia	1248	50	996	10.2	41422	4060	1621
UKH2	Bedfordshire and Hertfordshire	1414	77	1051	9.7	27648	2532	1444
UKH3	Essex	1443	80	992	11.3	38064	3737	2044
UKI1	Inner London - West	2063	64	1891	9.1	58138	2974	1754
UKI2	Inner London - East	4155	79	2849	19.6	116507	3989	2158
UKJ1	Berkshire, Buckinghamshire and Oxfordshire	1138	48	710	15.8	64021	8921	2654
UKJ2	Surrey, East and West Sussex	1544	54	1144	13.5	50870	4346	1732
UKJ3	Hampshire and Isle of Wight	1001	51	772	11.9	31357	3960	1549
UKJ4	Kent	1254	69	879	7.8	31617	3498	1684
UKK1	Gloucestershire, Wiltshire and Bristol/Bath area	1088	44	859	15.8	41523	4731	1643
UKK2	Dorset and Somerset	256	19	271	11.2	12210	4407	903
UKK3	Cornwall and Isles of Scilly	247	44	245	8.5	7465	2943	1288
UKK4	Devon	262	22	261	16.8	15294	5760	1273
UKL1	West Wales and The Valleys	975	50	776	9.8	27188	3402	1347
UKL2	East Wales	576	50	462	9.7	14964	3142	1252
UKM2	Eastern Scotland	1002	24	952	17.0	54301	5603	1277
UKM3	South Western Scotland	1268	27	1237	10.7	82975	6609	1735
UKM5	North Eastern Scotland	139	28	148	7.8	4378	2851	861
UKM6	Highlands and Islands	150	32	145	9.4	5164	3454	1069
UKN0	Northern Ireland (UK)	163	6	318	14.2	31357	9763	1123

Table 9: Intra- and inter-regional trade for the UK NUTS2 regions

Region code	Region name	Domestic	Rest of UK	EU27	ROW
UKC1	Tees Valley and Durham	0.308	0.605	0.068	0.019
UKC2	Northumberland and Tyne and Wear	0.376	0.534	0.077	0.014
UKD1	Cumbria	0.356	0.579	0.060	0.005
UKD3	Greater Manchester	0.408	0.535	0.044	0.013
UKD4	Lancashire	0.305	0.638	0.050	0.007
UKD6	Cheshire	0.596	0.254	0.043	0.107
UKD7	Merseyside	0.562	0.339	0.061	0.038
UKE1	East Yorkshire and Northern Lincolnshire	0.380	0.565	0.049	0.006
UKE2	North Yorkshire	0.347	0.604	0.042	0.006
UKE3	South Yorkshire	0.308	0.617	0.071	0.004
UKE4	West Yorkshire	0.382	0.559	0.051	0.007
UKF1	Derbyshire and Nottinghamshire	0.333	0.613	0.044	0.011
UKF2	Leicestershire, Rutland and Northamptonshire	0.392	0.552	0.047	0.010
UKF3	Lincolnshire	0.287	0.660	0.047	0.005
UKG1	Herefordshire, Worcestershire and Warwickshire	0.358	0.588	0.044	0.010
UKG2	Shropshire and Staffordshire	0.340	0.622	0.034	0.004
UKG3	West Midlands	0.385	0.529	0.061	0.024
UKH1	East Anglia	0.413	0.506	0.047	0.034
UKH2	Bedfordshire and Hertfordshire	0.354	0.545	0.071	0.029
UKH3	Essex	0.310	0.593	0.071	0.026
UKI1	Inner London - West	0.452	0.388	0.079	0.081
UKI2	Inner London - East	0.334	0.497	0.075	0.094
UKJ1	Berkshire, Buckinghamshire and Oxfordshire	0.451	0.449	0.062	0.038
UKJ2	Surrey, East and West Sussex	0.357	0.504	0.070	0.069
UKJ3	Hampshire and Isle of Wight	0.429	0.503	0.040	0.027
UKJ4	Kent	0.345	0.566	0.056	0.033
UKK1	Gloucestershire, Wiltshire and Bristol/Bath area	0.396	0.529	0.041	0.033
UKK2	Dorset and Somerset	0.304	0.635	0.039	0.022
UKK3	Cornwall and Isles of Scilly	0.359	0.586	0.045	0.010
UKK4	Devon	0.346	0.594	0.038	0.022
UKL1	West Wales and The Valleys	0.303	0.621	0.046	0.029
UKL2	East Wales	0.331	0.627	0.035	0.007
UKM2	Eastern Scotland	0.401	0.533	0.032	0.034
UKM3	South Western Scotland	0.430	0.507	0.032	0.030
UKM5	North Eastern Scotland	0.616	0.343	0.035	0.006
UKM6	Highlands and Islands	0.398	0.545	0.047	0.010
UKN0	Northern Ireland (UK)	0.426	0.493	0.048	0.033

Table 10: Additional results with ρ constant

Region code	Region name	Total	Increase (%)	Lives saved*	Total	Increase (%)	Lives saved*
EU27	European Union	4485729	4088	200	157732	47	2
UK	United Kingdom	55005	80	34	1234811	3939	1700
UKC1	Tees Valley and Durham	1146	56	34	19367	2530	1560
UKC2	Northumberland and Tyne and Wear	1314	59	34	22135	2577	1473
UKD1	Cumbria	609	89	57	6137	1803	1166
UKD3	Greater Manchester	2185	32	19	63746	3739	2225
UKD4	Lancashire	1178	55	28	22501	2854	1462
UKD6	Cheshire	733	45	25	21427	4145	2264
UKD7	Merseyside	1424	55	33	28803	3032	1809
UKE1	East Yorkshire and Northern Lincolnshire	791	93	41	9714	2276	1001
UKE2	North Yorkshire	661	87	38	13801	3814	1644
UKE3	South Yorkshire	1189	51	29	24371	2993	1697
UKE4	West Yorkshire	1541	47	21	46383	4310	1970
UKF1	Derbyshire and Nottinghamshire	1572	61	27	49362	4952	2212
UKF2	Leicestershire, Rutland and Northamptonshire	1459	69	33	35357	3998	1903
UKF3	Lincolnshire	616	160	51	6282	2552	808
UKG1	Herefordshire, Worcestershire and Warwickshire	1089	67	33	25535	3822	1860
UKG2	Shropshire and Staffordshire	1249	53	27	29621	3535	1785
UKG3	West Midlands	2370	36	22	63226	3540	2132
UKH1	East Anglia	2096	110	44	40850	4003	1598
UKH2	Bedfordshire and Hertfordshire	1694	61	35	27255	2495	1423
UKH3	Essex	1878	89	49	37781	3709	2028
UKI1	Inner London - West	3087	63	37	57793	2956	1743
UKI2	Inner London - East	4202	47	26	116046	3973	2149
UKJ1	Berkshire, Buckinghamshire and Oxfordshire	1302	83	25	63897	8903	2649
UKJ2	Surrey, East and West Sussex	2075	81	32	50388	4304	1715
UKJ3	Hampshire and Isle of Wight	1427	85	33	30980	3911	1530
UKJ4	Kent	1710	95	46	31275	3459	1666
UKK1	Gloucestershire, Wiltshire and Bristol/Bath area	1398	63	22	41123	4685	1627
UKK2	Dorset and Somerset	937	246	50	11700	4219	864
UKK3	Cornwall and Isles of Scilly	597	143	63	7280	2867	1255
UKK4	Devon	728	179	40	14927	5620	1242
UKL1	West Wales and The Valleys	1442	86	34	26730	3343	1324
UKL2	East Wales	841	82	33	14680	3080	1227
UKM2	Eastern Scotland	2262	138	31	53068	5474	1248
UKM3	South Western Scotland	3396	175	46	82058	6535	1715
UKM5	North Eastern Scotland	401	170	51	4168	2709	818
UKM6	Highlands and Islands	503	246	76	4893	3268	1011
UKN0	Northern Ireland (UK)	1903	499	57	30150	9384	1079