COVID-19 Crisis Management in Luxembourg: Insights from an Epidemionomic Approach

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Abstract. – We develop an epidemionomic model that jointly analyzes the health and economic responses to the COVID-19 crisis and to the related containment and public health policy measures implemented in Luxembourg and in the Greater Region. The model has a weekly structure and covers the whole year 2020. With a limited number of parameters, the model is calibrated to depict the pre-crisis evolution of the Luxembourg economy, and to match post-lockdown leading economic indicators and industry-specific infection curves. The nowcasting part of our analysis reveals that each week of lockdown reduces national output by about 28% (and annual GDP by 0.54%). A first peak of the infection curve was observed at the very beginning of April. If the lockdown measures had been permanent, annual GDP would have decreased by 22% in 2020, the number of COVID-19 cases would have reached zero around mid-June, and the proportion of recovered people would have reached 1.4% of the population. In an economy heavily relying on skill-intensive services, we show that the role of teleworking has been instrumental to limiting the weekly economic output loss (almost by one half) and the propagation of the virus. In the forecasting part of the analysis, we quantify the epidemiological and economic responses to gradual deconfinement measures under various public health scenarios. If the post-lockdown transmission rates could be kept constant throughout the deconfinement period, restarting all sectors would have huge effects on the economy (limiting the annual GDP loss to about 7%) and no effect on the aggregate infection curve. While it is a good time for lifting containment measures, there is also a risk that increasing the density of employees at the workplace and resuming social activities would induce a rebound in the infection curve. Preventing such a relapse is possible with PCR testing of both national and cross-border workers, and with accompanying measures such as (i) maintaining teleworking practices, (ii) reopening hotels, restaurants and cafés at half of their full capacity or with equivalent physical distancing measures and last but not least, (iii) sustaining distancing measures in social activities. Overall, in our worst-case scenario, combining bi-monthly testing with contact tracing and quarantining measures appear to be a sufficient (perhaps not necessary) policy option in the aftermath of the deconfinement plan.

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1 Introduction

The COVID-19 pandemic has affected people’s health and economic indicators all around the globe. Focusing on Luxembourg’s economy and workers from the Greater Region, we analyze here the public health and economic effects of the COVID-19 crisis week after week throughout the year 2020. We develop an *epidemionomic* model that combines an extended Input-Output economic block with a SIIR epidemiological block, and use it to quantify the effects of lockdown measures as well as of the ongoing deconfinement plan. We treat economic and epidemiological trends as interdependent, which is justified for several reasons. Firstly, it has been abundantly documented that *non-pharmaceutical* measures implemented in March have affected public health and economic indicators jointly. In particular, lockdown and social distancing measures were necessary to flatten the infection curve and avoid a collapse of the health care system, while generating a disciplined and sizeable cut in economic output. Secondly, after the phase of lockdown measures, policymakers have been implementing gradual measures to restart the economy. Lifting containment measures induces changes in employment which in turn, revive on-the-job interactions between workers as well as between workers and customers. Depending on PCR testing policies, contact tracing, social distancing, hygiene and prevention measures at the workplace and in social activities, these interactions affect the propagation of the virus within the country as well as in the cross-border regions where about one half of the labor force lives. In turn, changes in infection rates in the Greater Region affect the number of workers available for the labor market and potential employment levels.

Uncertainty around the scale of these interactions and around the effectiveness of lockdown and deconfinement plans remains substantial. We use our epidemionomic model to produce nowcasts of the costs of the crisis, and simulation results that can inform public decisions about the relevant modalities and timing/extent of the restarting strategy. As far as the cost of the lockdown is concerned, OECD (2020) and RECOVid (2020) provide rough estimates of the short-term effect of the COVID-19 crisis in Luxembourg assuming a post-crisis gradual return to normalcy (i.e., disregarding the possibility of a systemic collapse of the global/European financial markets as well as drastic behavioral changes). In this study, we refine these estimates using additional post-lockdown economic indicators and firm-level survey data.

Turning to the lifting of containment measures, any deconfinement plan targets two objectives: minimizing the risk of relapse of the health crisis, and maximizing the economic benefits from lifting containment measures in some industries. Maximizing economic benefits of gradual deconfinement measures is important to restore confidence in the future, to reinforce trust in democracy, to help the State sustain generous budget support policies to firms and

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1The double “I” in SIIR means that our compartmental epidemiological block distinguishes between infected people with symptoms and those who are asymptomatic. In our model, we assume the former get detected while the latter don’t. We disregard deaths as mortality is low among the working-age population; we do not distinguish between exposed and susceptibles (as in a SEIR model); and we assume that all recovered remain immune (unlike in a SEIRS model).

2Some have seen lockdown measures as resulting from a tradeoff between public health and economic objectives (Barro et al., 2020; Gourinchas, 2020). This tradeoff is much more ambiguous than it is apparent as the recession could have been deeper without the lockdown, as evidenced from the 1918 Spanish flu (Correia et al., 2020). It is hard to identify whether the measures implemented to curb the infection curves contribute to increase or decrease confidence in the economic system. A severe public health crisis alone can generate panic and (potentially drastic) changes in individual behaviors. Many economic crises were associated with panics from depositors or from the banking sector.
households, or to minimize the risk of financial distress and rising poverty/inequality. Minimizing the risk of relapse is important to avoid congestion in the healthcare system and to help workers overcome the fear of being contaminated. Several risk-minimizing strategies to bring workers back to work and unfold the return of economic activity have been discussed in recent works. For example, age, region or immunity criteria could be chosen to control the conditions for gradual release from containment. The proposed strategies are not implementable easily and directly in the case of Luxembourg, an open economy that heavily relies on cross-border commuting flows. In addition, the health and economic responses to deconfinement policies depend on accompanying measures in terms of physical distancing, prevention, hygiene, testing, tracking or contact tracing. Our model can be used to assess the sensitivity of the public health and economic effects of deconfinement plans to many accompanying measures.

We produce results by period of one week throughout the entire year 2020. We distinguish three important phases. The first one is the **pre-disease phase** and is mostly associated with the deterioration of the global economy and the disruption of global supply value chains. The news on COVID-19 started to rampantly spread across various media in China from January 21st. Two days later, Wuhan – the capital city of Hubei Province and the epicenter of China’s coronavirus outbreak – was locked down. This drastic measure urged other Chinese provinces to implement containment measures, which exerted negative influence on the Chinese economy as well as cascading effects on the World economy. The economic damages have begun to materialize since the beginning of the year. They were relatively small given the size of the sectors involved, and gradually increased as negative demand shocks started to hit sectors such as tourism, air transport, hospitality and entertainment. The second one is the **lockdown phase**, which started early March in Italy and mid-March in Luxembourg. This phase is characterized by negative demand and supply shocks resulting from containment measures, school closures, financial disturbances and a drop in social consumption. The third one is the **restarting phase**, which started on April 20th with the reopening of construction sites. These measures should mark the beginning of the economic recovery, although the latter can be muted by hysteresis if the lockdown phase results in a large number of payment defaults and bankruptcies. In the case of Luxembourg, budget support policies conducted during the lockdown have relieved corporate cash flow and household income, maintaining the economy in a satisfactory state of hibernation. Our quantitative exercise relies on the assumption that a return to normalcy is plausible.

The restarting phase will extend over several stages in Luxembourg and a rebound in the infection curve could slow down the unrolling of the different phases. The first restarting stage, which started on April 20th, involves the reopening of construction sites, hardware stores, gardeners and landscape businesses and recycling centers. From May 4, schools reopen for a fraction of students and pupils, starting with graduating classes in the secondary education, practical exercise classes and internships at University and for the Advanced Technician

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3See Section 2.8 in *RECOVid (2020).*

4Baldwin and Weder di Mauro (2020) argued: “this virus is as economically contagious as it is medically contagious.” As the production of basic and intermediate goods in some countries is put on hold, the production of more advanced goods is also paralyzed. These disruptions induce shortages, especially, but not exclusively, in the healthcare sector, and result in surges in prices and competition between consumers and between countries.

5On March 16, schools were closed in Luxembourg. The government ruling from March 18 defined which business activities had to close as well as the social distancing measures to be followed. Construction sites had to be closed by March 20.

6Reduced oil prices act as a partial stabilizer, while other international spillovers are clearly negative.
Certificates (BTS). In the second restarting stage, starting on May 11th, secondary schools and most economic activities reopen, from shops to (most) museums and libraries. Restaurants maintain take-out and delivery services only. Indoor activities such as fitness clubs, swimming pools, cinemas, concert halls and theaters also remain closed. Gatherings remain forbidden until July 31st, with the exception of funerals and civil weddings that can have an attendance of up to 20 people, conditional on the upholding of the 2 meter minimal distance between them. In the third stage, starting on May 25th, primary schools and childcare facilities reopen. Bars and restaurants are allowed to serve on terrace as of May 27th and inside as of May 29th, under some restrictions (distance of 1.5m between tables or protection when distancing is not feasible, maximum 4 people per table if not living within same household, closing at midnight, etc.). Nightclubs remain closed until further notice. Indoor pools, sports facilities and fitness centers are allowed to reopen with distancing measures, whereas saunas and spas remain closed until further notice. The national passenger airline, Luxair, restarts its first passenger flights on May 29th. Finally, cultural and religious events are allowed with a public exceeding 20 participants if the social distance of 2m between seated participants can be guaranteed. Places also need to be pre-booked, including for masses in churches. After the third deconfinement stage, the paradigm changes: everything is allowed (under rules of public health and social distancing) besides explicitly specified exceptions.7

We contribute to a recent and fast-growing literature linking public health and economic responses to the COVID-19 crisis. Part of the literature focuses on the dynamics of the disease, including the role of social-distancing (Greenstone and Nigam, 2020) and the quantification of the work that can be done from home in order to slow down the spread of the virus (see e.g., Barbieri et al., 2020; Dingel and Neiman, 2020; Koren and Peto, 2020). Alvarez et al. (2020) study a planner’s dynamic control problem who wants to limit fatalities of the pandemic while also minimizing its economics costs. An increasing number of papers adds epidemiological blocks to macro-economic models to evaluate the cost of the lockdown and different restarting strategies (Alvarez et al., 2020; Atkeson, 2020; Berger and Mongey, 2020; Jones et al., 2020). For example, Eichenbaum et al. (2020) extend the canonical epidemiological model to study how endogenous consumption and labor supply decisions of utility-maximizing agents affect contagion. The competitive equilibrium of their model is not socially optimal because infected individuals do not internalize how their actions amplify the spread of the virus. They simulate different confinement strategies and find that the best policy implies a severe recession but saves half a million lives in the US.

Fadinger and Schymik (2020) use an input-output model calibrated on Germany to evaluate the impact of work-from-home (henceforth referred to as teleworking) on infection risk and output at the regional level. Simulating a confinement where production is done exclusively by workers who can work-from-home, they find that confinement reduces labor supply by 58% and implies a weekly GDP loss equivalent to 1.6% of the annual GDP. Barrot et al. (2020) calibrate a standard network model using French input-output linkages. They estimate that a six weeks confinement in France led a drop in the active workforce of 52%, implying a loss of 5.6% of total GDP and a sectoral drop in value added varying between 8.8% to 4.1%. These two papers are similar in spirit to our strategy but our model also accounts for not confined economic activity in addition to teleworking. Moreover, our epidemiological block accounts for the spread of the virus outside the workplace in addition to differential infection rates of cross-border workers, a specificity of the Luxembourgish labor market. In addition, we provide different scenarios for demand shocks and the impact of international trade.

7See https://msan.gouvernement.lu/fr.
The remainder of this paper is organized as following. Section 2 describes the epidemiionomic model and its parameterization. Health and economic effects of the COVID-19 crisis and lockdown measures and restarting scenarios are investigated in Section 3. Section 4 concludes by summarizing the policy implications of our analysis.

2 An Epidemionomic Model for Luxembourg

We present here a model that reconciles the public health and economic sides of the COVID-19 crisis. We use it to predict the evolution of economic and public health variables over the year 2020. Our model assumes that one period consists of one week of time, which is assumed to correspond to the time of delivery of intermediate inputs from one industry to another.

2.1 Economic Structure

Economically speaking, total or partial lockdown measures have been implemented in several industries (accommodation and food services; arts, entertainment and recreation services; construction; wholesale, retail trade and repair services; and to a lesser extent in the manufacturing industry; transportation and storage services; real estate services). Given intersectoral linkages, these lockdown measures have gradually “contaminated” the other sectors of the economy, leading to complex effects. Similarly, lifting economic containment measures induces ripple effects on the rest of the economy. Large benefits from deconfinement arise in industries exhibiting the greater linkages with other sectors while simultaneously not suffering too much from disrupted global supply chains.

To account for intersectoral linkages, we develop here an extended input-output (I/O) model that accounts for both demand-side and supply-side mechanisms. This extended I/O framework is intended to characterize the functioning of the economy with fixed prices, fixed capital stocks, fixed technology and fixed workforce size by industry (i.e., no intersectoral mobility). Industries are denoted by \( i = 1, \ldots, I \). Before adding the time dimension, let us first focus on the (stationary) equilibrium of the model. The standard I/O model assumes that each sector’s output is determined by total demand – demand of intermediate inputs by other sectors, and demand for final goods by domestic and foreign actors. Typically, the total sales of industry \( i \) \( (X_i^d) \) are given by:

\[
X_i^d = \sum_j X_{ij} + D_i + E_i, \tag{1}
\]

where \( X_{ij} \) is the demand for intermediate inputs by industry \( j \), \( D_i \) is the domestic (Luxembourgish) demand for final goods, and \( E_i \) is the demand for exports.

The demand for intermediate inputs by industry \( j \) is assumed to be proportional to the total sales of that industry. We thus have \( X_{i,j} = a_{ij}X_j^d \), where the \( a_{ij} \)'s represent constant technological coefficients. Eq. (1) can be rewritten as:

\[
X_i^d = \sum_j a_{ij}X_j^d + D_i + E_i, \tag{2}
\]

which links the total sales of industry \( i \) to the total sales of all other industries.

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\(^8\)Eq. (2) corresponds to a row of the I/O matrix.
Using matrix notations and denoting the matrix of technological coefficients by $A$, this gives $X^d = AX^d + D + E$ which represents a system of $I$ equations. The well-known solution of the standard I/O model is given by $X^d = (1 - A)^{-1}(D + E)$. In this framework, a positive demand shock in industry $i$ generates a direct increase in output. This increases the demand for intermediate inputs addressed to the other sectors, which in turn increase their own demand for intermediate inputs and thereby generate indirect effects on the economy. The exact opposite mechanism arises when the economy is subject to a negative demand shock. The larger the linkages with the other sectors (i.e., the larger the $a_{ij}$’s), the larger the total effect on the economy.

The implicit assumption of the I/O model is that each sector can respond to the rising demand from the other sectors and from final consumers by producing more. The supply side of the model can be re-expressed as:

$$X^s_i = \sum_j X_{ji} + Y_i + M_i,$$

where the first term of the sum represents the domestic demand for intermediate inputs by industry $i$, $Y_i$ is the value added in industry $i$, whose production requires using $K_i$ units of physical capital and $L_i$ workers (i.e., $Y_i = F(K_i, L_i)$), and $M_i$ is the demand for foreign inputs. Assuming that imports are proportional to total sales, $M_i = m_i X^s_i$, the supply-side of the model can be re-expressed as:

$$X^s_i = \left[\sum_j a_{ji} + m_i\right] X^s_i + Y_i = \frac{Y_i}{1 - \sum_j a_{ji} - m_i}. \quad (3)$$

Total sales are proportional to the value added.

If $K_i$ is fixed, the only variable of adjustment that firms can use is $L_i$, the level of employment. Hence, supply follows demand, and firms adjust the level of employment to meet total demand for their product. Hence, $L^d_i = F^{-1} \left[X^d_i \left(1 - \sum_j a_{ji} - m_i \right)\right]$. Firms have the capacity and incentive to reach this level of employment if $L^d_i$ is smaller than the supply of labor in industry $i$, $L^s_i$, corresponding to a maximal value added of $Y^s_i$ and a maximal level of total sales of $X^s_i$. In the standard I/O model, supply follows demand because $X^d_i < X^s_i$ (or equivalently, $Y^d_i < Y^s_i$) by assumption. Firms in industry $i$ increase their value added ($Y^d_i$) and their imports ($M_i$) without constraints to meet demand for their goods. The supply-side plays no role, except that it determines how revenues are distributed between capital owners, workers, domestic and foreign suppliers of intermediate goods.

When modeling the effect of the COVID-19 crisis and of lockdown measures, we need to enrich the standard model with binding supply-side constraints. Firstly, some workers are infected by COVID-19 and cannot supply labor. Secondly, in addition to infection, school closures imply that many workers are forced to take parental leave. Thirdly, containment measures reduce the permitted level of employment in lockdown industries. Hence, the

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9 This equation corresponds to a column of the I/O matrix.

10 In the Cobb-Douglas case, we have $Y_i = B_i K_i^{1-\alpha_i} L_i^{\alpha_i}$ where $\alpha_i$ is the labor income share in industry $i$, and $B_i$ denotes total factor productivity.

11 Furthermore, we also assume that $L^s_i$ is smaller than the optimal level of employment $L^*_{it}$ (corresponding to a value added of $Y^*_{it} = F(K_{it}, L^*_{it})$ and a level of total sales of $S^*_{it}$). The latter level is determined by profit maximization. Firms in industry $i$ would like to increase employment up to the level $L^*_{it}$ (such that the marginal productivity of labor $F_{L_i}$ equals the wage rate $w_i$) and to produce a value added of $Y^*_{it} = F(K_{it}, L^*_{it})$. In the Cobb-Douglas case, we have $L^*_{it} = (\alpha_i B_i/w_i)^{1/(1-\alpha_i)} K_i$ and $Y^*_{it} = (\alpha_i B_i/w_i) L_i$. 


maximal level of employment during the lockdown ($L_{si}$) decreases, and this determines the maximal levels of value added $Y_{si}$ and of sales $X_{si} = \frac{Y_{si}}{1-\sum_j a_{ji} - m_i}$ in industry $i$ as in Eq. (3). The level of $L_{si}$ will be endogenized in the next section.

Starting from the pre-crisis stationary equilibrium, we simulate the effect of the crisis and resulting lockdown measures on activity. Two important ingredients govern our simulated trends. First, we assume that each iteration of the I/O matrix takes one week of time. Final demand is met instantaneously when supply constraints allow for it, while supplying intermediate inputs involve a delivery delay of one period. We thus include a time subscript $t$ into the notations. Second, at each iteration, we combine demand and supply constraints. The dynamics of the extended I/O model with supply-side constraints is now characterized by:

$$X_{i,t+1} = \min \left[ X_{s,i,t+1}, \sum_j a_{ij} \min \left( X_{d,j,t}, X_{s,j,t} \right) + D_{i,t+1} + E_{i,t+1} \right].$$

(4)

Given the parameters of the Luxembourg I/O table and the economic/health induced by COVID-19, the simulated solution of this model determines the endogenous production regime of each industry (excess supply or constrained supply capacity) as well as industry-specific multiplier effects. For industries in excess supply capacity, demand determines the total level of sales which, in turn, determines the level of employment and value added. For industries in constrained supply capacity, the maximal level of employment determines the value added which in turn, determines the total amount of sales.

As stated above, the existence of supply constraints induces a disciplined and sizeable cut in output... but also limits the magnitude of the I/O multiplier. This is beneficial to the economy when the lockdown is concomitant with a fall in final demand (e.g., due to a fall in exports). This slows down the recovery when some confined sectors are restarted or when final demand increases.

2.2 Epidemiological Structure

Our epidemiological block consists of a compartmental model that decomposes the sector-specific labor force available at week $t$ into sixteen groups. These involve 4 regions of residence $O = (L, F, G, B)$ for Luxembourg, France, Germany and Belgium, and four infection groups. More precisely, we have three infection status: $L_{i,t}^{OS}$ non infected individuals from origin $O$, $L_{i,t}^{OR}$ recovered, and $L_{i,t}^{OI}$ infected individuals. The stock $L_{i,t}^{OI}$ includes workers who are infected and infectious. Not all of these workers are sick and symptomatic. The latter group is split into two sub-groups: a fraction $\theta$ of asymptomatic individuals ($L_{i,t}^{OIa} = \theta L_{i,t}^{OI}$) and a fraction $(1-\theta)$ of symptomatic individuals ($L_{i,t}^{OIv} = (1-\theta) L_{i,t}^{OI}$). Ignoring deaths among the working-age population and inter-industry mobility, the total labor force by sector $L_{i,t} = L_{i,t}^{OS} + L_{i,t}^{OR} + L_{i,t}^{OIa} + L_{i,t}^{OIv}$ is constant over time.

Suppose that sick and symptomatic workers self-isolate as soon as they feel the symptoms. As symptoms are felt a few days after becoming infectious (say 2.5 to 3 days), a fraction $\mu_{i,t}^{v}$ of symptomatic workers go to their workplace while being contagious if PCR testing is not

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12 The standard SIR model assumes immunity is obtained after having been infected and is permanent. The duration of immunity from COVID-19, if any, is not determined yet. Model predictions are thus valid either for time periods as long as the duration of the acquired immunity, or for regimes where the total number of infected does not represent a considerable fraction of the population.
performed on a daily basis. Some individuals are asymptomatic during the whole cycle of the disease and never self-isolate. A fraction $\mu_{a,i,t}$ of asymptomatic workers go to their workplace. The fractions $(\mu_{v,i,t}, \mu_{a,i,t})$ depend on the efficiency and frequency of PCR testing as well as contact tracing.

The quantity of workers available in Luxembourg and in industry $i$ is defined as:

$$L_s^{i,t} = \sum_O \phi_{i,t} (1 - \lambda_{O,i,t}^{O}) \left( L^{OS}_{i,t} + L^{OR}_{i,t} + \mu_{a,i,t} L^{OIa}_{i,t} + \mu_{v,i,t} L^{IOv}_{i,t} \right),$$  

where $\phi_{i,t}$ is the lockdown constraint on employment ($\phi_{i,t} < 1$ in lockdown industries and $\phi_{i,t} = 1$ in the others), $\lambda_{O,i,t}^{O}$ is the share of workers in parental leave, equal to the share of parents with young children when schools are closed in region $O$, and zero if schools fully re-open. A total lockdown would imply that $\phi_{i,t} = 0$. In practice, a minimal level of post-lockdown activity is observed in all sectors, either because the lockdown applies to a sub-sector only, or because entrepreneurs find ways to maintain a certain level of output by re-orienting their activity (e.g., restaurants providing catering services with delivery at home). As $\mu_{v,i,t} \leq 1$, Eq. (5) clearly shows that a rise in the number of infected workers decreases the supply of labor and potentially influences the level of economic activity.

The dynamics of these stocks is governed by virus transmission rates on the job and in the place of residence. In each sector, the rate of presence at the workplace is denoted by:

$$e_{i,t} = \min\left( \frac{L^d_{i,t}}{L_{i,t}}, \frac{L^s_{i,t}}{L_{i,t}} \right) (1 - \tau_{i,t}),$$  

where the fraction is meant to represent the employment rate (equal to unity if the sector is not supply- or demand-constrained and smaller than unity otherwise) and $\tau_{i,t}$ denotes the share of workers in situation of teleworking in sector $i$. When $e_{i,t}$ is smaller than unity, we assume that employees present at the workplace are randomly drawn from the labor force distribution, which means that the share of infected employees is equal to the share of infected workers in $L^s_{i,t}$.

When workers are fully employed, the daily amount of time spent interacting with others is shared between a fraction $\epsilon$ on-the-job, and a fraction $(1 - \epsilon)$ in the place of residence. This is because the number of contacts and physical distancing practices differ among these two locations. When workers are fully unemployed, the total amount of time spent interacting with others is spent in the place of residence. More generally, if the employment rate is between zero and one, these fractions of interaction time spent on the job and in the place of residence are equal to $\epsilon e_{i,t}$ and $(1 - \epsilon e_{i,t})$, respectively. We thus have:

$$\begin{cases}
L^{OS}_{i,t+1} = L^{OS}_{i,t} - \epsilon e_{i,t} b_{i,t} L^{OS}_{i,t} \sum_O L^{OI}_{i,t} - (1 - \epsilon e_{i,t}) b_{i} L^{OS}_{i,t} P^{OI}_{t} P_t^{-} \\
L^{OI}_{i,t+1} = L^{OI}_{i,t} + \epsilon e_{i,t} b_{i,t} L^{OI}_{i,t} \sum_O L^{OI}_{i,t} + (1 - \epsilon e_{i,t}) b_{i} L^{OI}_{i,t} P^{OI}_{t} P_t^{-} - G^{OR}_{i,t} \\
L^{OR}_{i,t+1} = L^{OR}_{i,t} + G^{OR}_{i,t},
\end{cases}$$

where $G^{OR}_{i,t}$ is the flow of recovered from origin $O$ in week $t$, $b_{i,t}$ is the on-the-job virus transmission rate in sector $i$, and $b^{O}_{t}$ is the virus transmission rate at the place of residence in country $O$. These parameters are defined over a period of one week in our model.

In the case of COVID-19, infected people recover after 10 days on average. In a model with a daily structure, we would define the number of recovered as the number of new contagious
cases nine days before. Here, the weekly structure of our model implies that the flow of recovered during week $t$ is a weighted sum of the flow of contagious cases in weeks $t - 1$ and $t - 2$. Following analytical developments in Appendix A and under the hypothesis of a uniform distribution of new contagious cases within a week, the weekly flows of recovered from origin $O$ in industry $i$ during period $t$ can be approximated by:

$$G_{i,t}^{OR} = \frac{2}{7} \left[ \epsilon e_{i,t-2} b_{i,t-2} \frac{L_{i,t-2}^{OS} \sum O L_{i,t}^{OI}}{L_{i,t-2}} + \left(1 - \epsilon e_{i,t-2}\right) b_{i}^{O} L_{i,t-2}^{OS} \frac{P_{i,t-2}^{OI}}{P_{i,t-2}} \right] + \frac{5}{7} \left[ \epsilon e_{i,t-1} b_{i,t-1} \frac{L_{i,t-1}^{OS} \sum O L_{i,t-1}^{OI}}{L_{i,t-1}} + \left(1 - \epsilon e_{i,t-1}\right) b_{t-1}^{O} L_{i,t-1}^{OS} \frac{P_{i,t-1}^{OI}}{P_{i,t-1}} \right]. \quad (8)$$

We numerically show in Appendix A that predicting the weekly flow of recovered using Eq. (8) improves the predictive power of the model in comparison with a probabilistic model relying on a constant recovery rate (i.e., $G_{i,t}^{OR} = g \times L_{i,t}^{OI}$). The reason is that, contrary to the flow of new infections within the week, the total stock of contagious people ($L_{i,t}^{OI}$) has no reason to be distributed uniformly over the 10 daily contagious cohorts: this stock increases fast during the first phase of the pandemic (i.e., when the number of COVID-19 cases increases rapidly), and decreases fast after the peak of the infection curve has been reached.

Turning our attention to transmission rates, we express them as:

$$\begin{align*}
\begin{bmatrix}
b_{i,t} \\
b_{i,t}^{O}
\end{bmatrix} &= \begin{bmatrix}
\tilde{b}_{i} \\
\tilde{b}_{i}^{O}
\end{bmatrix} \hat{e}_{i,t}^{x} \left[ (1 - \theta) \mu_{i,t}^{v} + \theta \mu_{i,t}^{a} \right] \\
\begin{bmatrix}
b_{i,t} \\
b_{i,t}^{O}
\end{bmatrix} &= \begin{bmatrix}
\tilde{b}_{i} \\
\tilde{b}_{i}^{O}
\end{bmatrix} \hat{O} \mu_{i,t}^{O},
\end{align*} \quad (9)$$

which allows to highlight the main determinants of virus propagation:

- On-the-job transmission rates depend on the average number of contacts per person and per unit of time, and on the probability that infected people have contacts with susceptible subjects. The probability that infected people can have contacts with susceptible subjects depends on the probability that a contagious worker goes to work, which is given by $\left[ (1 - \theta) \mu_{i,t}^{v} + \theta \mu_{i,t}^{a} \right]$ in Eq. (9). This probability depends on the share of asymptomatic cases ($\theta$) as well as on testing and tracing measures implemented to isolate infected workers ($\mu_{i,t}^{v}, \mu_{i,t}^{a}$).
- The number of contacts per unit of time in the work place is expressed as the product of $\tilde{b}_{i}$, an industry-specific parameter that reflects working conditions in normal times (i.e., physical proximity and exposure to disease), by $\rho_{i,t}$, a variable that can be normalized to unity at the beginning of the pandemic, and that captures prevention and physical distancing measures implemented in the industry. In addition, physical distancing might partly depend on the density of workers at the workplace (as proxied by $e_{i,t}$), a mechanism that is referred to as the intensive-margin effect of employment on transmission rates. A potential specification is $\rho_{i,t} = \tilde{\rho}_{i,t} e_{i,t}^{x}$ where $x$ is the elasticity of physical distancing to the presence of workers at the workplace.
- Similarly, in all regions of residence $O = (L, G, F, B)$, the number of contacts per unit of time spent outside the labor market can be expressed as the product of $\tilde{b}_{i}^{O}$ by $\mu_{i}^{O}$. Hence, two regions or countries sharing different economic and socio-demographic characteristics exhibit different levels of $\tilde{b}_{i}^{O}$, while $\mu_{i}^{O}$ is governed by nation-wide or local social distancing and prevention measures.\(^{13}\)

\(^{13}\)Although the model could be extended to account for the impact of cross-border workers on the risk to infect population at origin, this effect is likely to be limited because $(1 - \epsilon e_{i,t})$ is relatively small.
To close the model, we consider that the trajectories of $p^{\text{OI}}_{i,t}$ are exogenous outside Luxembourg (i.e., for $O = (G, F, B)$), whereas the trajectory of $p^{\text{LL}}_{i,t}$ is endogenous and given by the average of all industries:

$$p^{\text{LL}}_{i,t} = \frac{\sum_i L^{\text{LL}}_{i,t}}{\sum_i 1}.$$  (10)

In our setting, lifting economic containment measures in industry $i$ implies an increase in the rate of presence at the workplace ($\Delta e_{i,t}$) and a resulting rise in the weekly flow of infected workers that is governed by:

$$\frac{dL^{\text{OI}}_{i,t+1}}{de_{i,t}} = \epsilon \left[ b_{1,t} \frac{L^{\text{OS}}_{i,t} \sum_i L^{\text{OI}}_{i,t} P^{\text{OI}}_{i,t}}{L_{i,t}} - b^{0}_{1,t} \frac{L^{\text{OS}}_{i,t} P^{\text{OI}}_{t}}{P_{t}} \right] + xeb_{1,t} \frac{L^{\text{OS}}_{i,t} \sum_i L^{\text{OI}}_{i,t}}{L_{i,t}}.$$  (11)

Eq. (11) clearly shows that shocks in employment rates and teleworking practices influence the infection curve through two possible mechanisms. Changes in workers’ presence rate mechanically influence the number of detected case through the extensive margin – changes in time spent on the job, where exposition to the disease differs from that prevailing in the place of residence – and through the intensive margin – changes in physical distancing and transmission rates on the job due to the higher density of employees. If $x = 0$, changes in employment rates have no effect on transmission rates (at the intensive margin), although they affect the weight given to $b_{1,t}$ relatively to $b^{0}_{1,t}$ in Eq. (7); this is the first term of the derivative above. In such a setting, the lockdown-driven decrease in $b_{1,t}$ can be considered as permanent. In contrast, if $x > 0$, part of that decrease in transmission rate is lost when workers get back to their workplace; this is the second term of the derivative.

### 2.3 Parameterization

We explain here our parameterization strategy. Our epidemionomic model is an evolving tool that aims to promptly deliver initial results at first, and then increasingly more refined results and predictions as the set of available data on socioeconomic variables and leading indicators increases. The model developed here not only matches the economic structure observed before the crisis (say, in December 2019), but also matches post-lockdown data obtained from administrative sources (ADEM, IGSS, etc.) and from firm-level surveys (Chamber of Commerce, Chambre des Métiers). Our modeling outputs can frequently be updated throughout the course of the crisis and of the potential recovery. In the next two sections, the parameterized model will be used to quantify the effect of the COVID-19 crisis on the Luxembourg economy and population, and to simulate the effects of deconfinement measures.

**Parameterization of the economic block.** – Our economic block is calibrated to match the I/O table of 2017. This table defines the matrix of technical coefficients ($a_{ij}$) and provides initial values for the industry-specific levels of sales ($X_{i,0}$), value added ($Y_{i,0}$), employment ($L_{i,0}$), stock of physical capital ($K_{i,0}$), imports ($M_{i,0}$), exports ($E_{i,0}$) and domestic demand ($D_{i,0}$). The production side of the model relies on the assumption that the production technology is Cobb-Douglas in each sector: $Y_{i,t} = B_{i,t} K^{\alpha_i}_{i,t} L^{1-\alpha_i}_{i,t}$. The parameter $\alpha_i$ captures the share of capital income in value added, and the total factor productivity level is calibrated as a residual ($B_{i,t}$). The first three columns of Table 1 give the pre-crisis level of employment and the calibrated parameters ($\alpha_i, B_{i,t}$) for all sectors.
Social security data (IGSS) distinguish between workers living in Luxembourg and those living in the neighboring countries. In addition, the SILC database splits cross-border workers by country of residence. Combining these two sources allows to identify workers originating from Luxembourg, Germany, France and Belgium. These numbers are reported in columns 4 to 7 of Table 1 for all sectors.

The rest of Table 1 characterizes economic changes observed between December 2019 and April 1, 2020. The number of workers in parental leave is estimated by STATEC to be the equivalent of a third of the individuals affected by temporary unemployment in total. The share of workers in parental leave \((\Delta \lambda_{it})\), is split across industries using SILC data on the proportions of workers aged below 30 and workers with children aged 6 to 15.\(^{14}\) The share of unemployed people \((\Delta u_{it})\) is obtained from ADEM, being aware that data on “chômage partiel” refer to forecasted applications and might overestimate the real extent of the employment effect.\(^{15}\) For the lockdown industries (i.e., manufacturing products; construction; wholesale and retail trade, repair services; transportation and storage services; accommodation and food services; real estate; arts, entertainment and recreation services; other services), we assume that the maximal employment rate corresponds to the post-lockdown (observed) rate, which allows us to compute \(\Delta \phi_{i,t}\) in column 9. The supply of labor in these industries is constrained by the containment measures. In the other industries, we have \(\Delta \phi_{i,t} = 0\). The share of employees working from home \((\Delta \lambda_{i,t})\) is depicted in column 10; data are taken from the recent survey conducted by the Chamber of Commerce. The same database provide proxies for the decrease in total sales as compared to the previous year \((\Delta X_{i,t}/X_{i,t})\), reported in the last column, and assumed to reflect the shock experienced by Luxembourgish firms at the very beginning of April.

As illustrated in Figure 1, changes in domestic demand and exports are relatively small before mid-March and become very important after the generalized lockdown in Europe. Figure 1a focuses on domestic demand. We assume a 2% decrease in domestic demand between the second mid-January and mid-February, followed by a 3% decrease between mid-February and mid-March. Then after the lockdown, we assume that the domestic demand for essential goods decreases by 20% and the demand for non essential goods decreases by 40%. The demand for health and social services decreases by 5% only. Changes in exports are depicted in Figure 1b. Changes in exports are calibrated to generate a 2% decrease in weekly GDP between mid-January and mid-March, in line with the recent forecasts described in STATEC (2020). After the lockdown, we distinguish between the lockdown and non-lockdown sectors. In non lockdown sectors, total demand determines sales and output. We calibrate the fall in exports so as to match the decrease in industry sales extracted from the survey of the Chamber of Commerce. The shocks varies between 15 and 50%, with the exception of ‘electricity, gaz and steam’, where exports almost fall to zero (note that in normal times, exports only account for 1/7 of total sales in this sector). In lockdown industries, production is supply-constrained and potential demand cannot be observed. We assume a 20% decrease in line with the recent forecasts of the Ifo institute.

In the most pessimistic scenario (referred to as permanent lockdown in Section 3.1), we assume that the decrease in exports and domestic demand is permanent. Less pessimistic

\(^{14}\)More precisely, we use a weighted mean of these two industry-specific shares defined as: 1/2 times workers below age 30 + 1/3 times workers with children aged 6-15.

\(^{15}\)This does not affect our GDP and total sales’ estimates, which match survey data from the Chamber of Commerce for the post-lockdown period (see below). However, overestimating concomitant employment changes translates into an underestimation of the decrease in total factor productivity.
scenarios about the global economy will also be considered in Section 3.1. The most optimistic scenario assumes that the levels of exports and imports are converging towards their pre-crisis levels between June and the end of 2020. The intermediate scenario assumes that half of the decreases in exports and imports will be recovered over the same period. In the deconfinement scenarios (Section 3), we assume that the recovery of domestic demand and exports is proportional to the recovery of GDP.

Figure 1: Change in final demand by industry under the permanent lockdown scenario

(a) Changes in domestic demand, $\left( \Delta D_{i,t}/D_{i,t} \right)$ (deviations from Dec 28, 2019)

(b) Changes in exports, $\left( \Delta E_{i,t}/E_{i,t} \right)$ (deviations from Dec 28, 2019)

Source: Authors’ hypotheses under the (most pessimistic) permanent lockdown scenario, which assumes that the decrease in exports, imports and domestic demand is constant from April to December 2020. The trajectory of imports and exports follows the Ifo scenario from January to March.
Table 1: Macroeconomic parameters by sector (as of April 1st, 2020)

<table>
<thead>
<tr>
<th>Sector</th>
<th>α</th>
<th>B</th>
<th>L_{i,t}</th>
<th>L^L_{i,t}</th>
<th>L^R_{i,t}</th>
<th>Δ(1 - λ_{i,t})</th>
<th>Δ(1 - U_{i,t})</th>
<th>Δ(1 - τ_{i,t})</th>
<th>ΔE_{i,t}</th>
<th>ΔD_{i,t}</th>
<th>ΔX_{i,t}</th>
</tr>
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<tbody>
<tr>
<td>Agric., forestry, fishing</td>
<td>0.511</td>
<td>0.042</td>
<td>3757</td>
<td>3222</td>
<td>203</td>
<td>-0.068</td>
<td>-0.159</td>
<td>-0.194</td>
<td>-0.491</td>
<td>-0.400</td>
<td>-0.300</td>
</tr>
<tr>
<td>Mining, quarrying</td>
<td>0.552</td>
<td>0.102</td>
<td>282</td>
<td>130</td>
<td>39</td>
<td>-0.068</td>
<td>0.000</td>
<td>-0.089</td>
<td>-0.372</td>
<td>-0.200</td>
<td>-0.200</td>
</tr>
<tr>
<td>Manufactured products</td>
<td>0.319</td>
<td>0.099</td>
<td>32193</td>
<td>9925</td>
<td>5736</td>
<td>-0.068</td>
<td>0.000</td>
<td>0.000</td>
<td>-0.313</td>
<td>-0.200</td>
<td>-0.200</td>
</tr>
<tr>
<td>Electricity, gas, steam</td>
<td>0.586</td>
<td>0.069</td>
<td>1727</td>
<td>1307</td>
<td>193</td>
<td>-0.068</td>
<td>0.000</td>
<td>-0.350</td>
<td>-0.543</td>
<td>-0.991</td>
<td>-0.500</td>
</tr>
<tr>
<td>Water, sewerage, waste</td>
<td>0.432</td>
<td>0.120</td>
<td>1823</td>
<td>951</td>
<td>200</td>
<td>-0.068</td>
<td>0.000</td>
<td>-0.184</td>
<td>-0.322</td>
<td>-0.498</td>
<td>-0.400</td>
</tr>
<tr>
<td>Construction</td>
<td>0.224</td>
<td>0.093</td>
<td>47962</td>
<td>20763</td>
<td>8743</td>
<td>-0.089</td>
<td>-0.947</td>
<td>-0.776</td>
<td>-0.060</td>
<td>-0.200</td>
<td>-0.850</td>
</tr>
<tr>
<td>Wholesale, retail, repair</td>
<td>0.602</td>
<td>0.283</td>
<td>54140</td>
<td>22950</td>
<td>6019</td>
<td>-0.066</td>
<td>-0.465</td>
<td>-0.388</td>
<td>-0.060</td>
<td>-0.200</td>
<td>-0.550</td>
</tr>
<tr>
<td>Transport, storage</td>
<td>0.211</td>
<td>0.078</td>
<td>31304</td>
<td>12707</td>
<td>6331</td>
<td>-0.079</td>
<td>0.000</td>
<td>-0.263</td>
<td>-0.285</td>
<td>-0.200</td>
<td>-0.400</td>
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<tr>
<td>Accommodation, food</td>
<td>0.127</td>
<td>0.053</td>
<td>21539</td>
<td>13459</td>
<td>874</td>
<td>-0.075</td>
<td>-0.765</td>
<td>-0.679</td>
<td>-0.103</td>
<td>-0.200</td>
<td>-0.800</td>
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<tr>
<td>Information, comm.</td>
<td>0.153</td>
<td>0.101</td>
<td>21661</td>
<td>10578</td>
<td>1492</td>
<td>-0.093</td>
<td>0.000</td>
<td>-0.105</td>
<td>-0.856</td>
<td>-0.482</td>
<td>-0.250</td>
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<tr>
<td>Financial, insurance</td>
<td>0.633</td>
<td>0.846</td>
<td>50128</td>
<td>26095</td>
<td>6647</td>
<td>-0.082</td>
<td>0.000</td>
<td>0.000</td>
<td>-0.700</td>
<td>-0.167</td>
<td>-0.150</td>
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<tr>
<td>Real estate</td>
<td>0.942</td>
<td>0.078</td>
<td>3869</td>
<td>2704</td>
<td>206</td>
<td>-0.087</td>
<td>-0.197</td>
<td>-0.084</td>
<td>-0.586</td>
<td>-0.200</td>
<td>-0.300</td>
</tr>
<tr>
<td>Prof, scient, techn</td>
<td>0.111</td>
<td>0.104</td>
<td>45017</td>
<td>23791</td>
<td>4578</td>
<td>-0.087</td>
<td>0.000</td>
<td>0.000</td>
<td>-0.798</td>
<td>-0.129</td>
<td>-0.200</td>
</tr>
<tr>
<td>Adminis, support</td>
<td>0.236</td>
<td>0.198</td>
<td>23862</td>
<td>11818</td>
<td>845</td>
<td>-0.087</td>
<td>0.000</td>
<td>-0.214</td>
<td>-0.363</td>
<td>-0.200</td>
<td>-0.350</td>
</tr>
<tr>
<td>Public administration</td>
<td>0.266</td>
<td>0.067</td>
<td>48627</td>
<td>45941</td>
<td>1343</td>
<td>-0.085</td>
<td>0.000</td>
<td>0.000</td>
<td>-0.416</td>
<td>-0.307</td>
<td>-0.150</td>
</tr>
<tr>
<td>Education</td>
<td>0.067</td>
<td>0.368</td>
<td>5560</td>
<td>39290</td>
<td>529</td>
<td>-0.100</td>
<td>0.000</td>
<td>0.000</td>
<td>-0.018</td>
<td>-0.900</td>
<td>-0.200</td>
</tr>
<tr>
<td>Health, social work</td>
<td>0.252</td>
<td>0.128</td>
<td>42854</td>
<td>27153</td>
<td>5092</td>
<td>-0.084</td>
<td>0.000</td>
<td>-0.019</td>
<td>-0.134</td>
<td>-0.200</td>
<td>-0.079</td>
</tr>
<tr>
<td>Arts, entertainment</td>
<td>0.133</td>
<td>0.108</td>
<td>2985</td>
<td>2652</td>
<td>311</td>
<td>-0.061</td>
<td>-0.258</td>
<td>-0.172</td>
<td>0.525</td>
<td>-0.200</td>
<td>-0.400</td>
</tr>
<tr>
<td>Other services</td>
<td>0.214</td>
<td>0.120</td>
<td>7567</td>
<td>5171</td>
<td>493</td>
<td>-0.061</td>
<td>-0.396</td>
<td>-0.327</td>
<td>-0.143</td>
<td>-0.200</td>
<td>-0.500</td>
</tr>
</tbody>
</table>

Notes: Cols. (1), (2): authors’ computations. Cols. (3) to (7): IGSS and SILC data. Col. (8) Δ(1 - λ_{i,t}): workers in parental leave from STATEC disaggregated by industry using IGSS data on workers aged 30 and less and workers with young children. Cols. (9): authors’ computations. Col. (10): data on “choyage partiel” from IGSS. Col. (11): data on teleworking from the survey conducted by Chamber of Commerce in April. Col. (12): authors’ computations based on the I/O matrix; Cols (13): authors’ hypotheses distinguishing between essential and non essential goods. Col (14): author’s computation based on the survey conducted by Chamber of Commerce in April.
Parameterization of the epidemiological block. – In our SIIR compartmental model, transmission rates are calibrated to match data on the cumulated number of detected COVID-19 cases by sector. Daily data on COVID-19 cases by sector and by region of residence are available from the IGSS database from the beginning of March until May 25. As our model does not include people who are not registered to IGSS (i.e., inactive and dependent individuals), we re-scale the number of infected individuals by sector so that the total number of infected people living in Luxembourg exactly matches the total number of COVID-19 cases in the Luxembourg population. We apply the same rescaling factors to cross-border workers. We aggregate COVID-19 cases per week, creating a database of 13 weeks times 19 sectors (247 observations) corresponding to $L^O_{it}$ in Eq. (7) (see Figure 2). Over the same period, we also use data on the region-wide shares of infected cases in the Greater Region (Rhineland-Palatinate and Saarland for Germany, Grand Est for France, and Wallonia for Belgium, see Figure 3).

The philosophy of our parameterization is to rely on a limited number of parameters and fitting assumptions. Many epidemiological models rely on complex polynomial functions to fit many daily data points. Obviously, the higher the number of parameters, the better the fit. This does not mean that the predictive power of such complex models is satisfactory – at least over sufficiently long periods of time – and that these models can predict the effects of out-of-trend shocks such as a deconfinement or the implementation of a new public health policy measures. A more structural approach such as ours is worth investigating. We fit the 19 infection curves by estimating 2 parameters per sector (i.e. 19 times 2 parameters), and 2 parameters per region of residence (i.e. 4 times 2 parameters). The industry-specific and origin-specific parameters consist of transmission rates in force at the beginning of the pandemic (denoted by $b_{i,1}$ and $b_{O,1}$) and after the lockdown (denoted by $b_{i,2}$ and $b_{O,2}$). To improve the fit of the infection curves, we assume the decrease in $b_{i,t}$ materializes within two weeks, half of it between March 9th and 16th, and half of it between March 16th and 23rd.

The calibration of the parameter set $\Gamma = (b_{i,1}, b_{i,2}, b_{O,1}, b_{O,2})$ relies on the Simulated Method of Moments, which identifies model’s transmission rates to make simulated model moments ($\hat{L}^O_{it}(\Gamma)$) match data moments ($L^O_{it}$):

$$\min_{\Gamma} \Lambda = \sum_{i} \sum_{O} \sum_{t} \left( \hat{L}^O_{it}(\Gamma) - L^O_{it} \right)^2.$$  

Figure 2 compares our estimated infection curves (dashed black curves) with data on COVID-19 cases by sector (gray curves). Our fit is excellent in all sectors except those with a very small number of detected COVID-19 cases (agriculture, mining and quarrying, arts and entertainment). In these sectors, transmission rates outside the labor market generate detected cases that exceed actual numbers. As illustrated on the bottom-right graph, our model almost perfectly matches the evolution of the aggregate number of detected COVID-19 case in the Luxembourgish workforce.

The top-left panel of Figure 3 shows the evolution of $b_{i,t}$, whereas the bottom-left panel shows the evolution of $b_{O,t}$. The highest levels of $b_{i,1}$ are obtained in health and social services, public administration, financial and insurance services. The rate is nil in four sectors – agriculture, mining and quarrying, electricity, and real estate services – that are not represented in the figure. These are sectors where the number of contagious individuals is small and is totally explained by transmission rates at the place of residence. In Section B in the Appendix, we correlate calibrated transmission rates with indices of exposure to risk by industry – reflecting heterogeneity in workers’ exposure to disease and physical distance at work. We find a high
level of correlation (around 0.6), suggesting that our identified $b_{i,1}$’s are meaningful (see Figure B.1).\textsuperscript{16} The top-right panel in Figure 3 shows the evolution of the recovery rate, defined as $g_{i,t} = C_{i,t} / L_{i,t}$. Contrary to a probabilistic model, these rates vary across industries and periods. They are low at the beginning of the pandemic as the first infected individuals recover after 10 days; they are peaking 10 days after the lockdown. The slight rebound in the number of detected cases observed in the first week of May translates into a temporary drop in recovery rates. The evolution of $b_{i,0}^O$ is similar across origin regions. The bottom-right panel of the figure shows the evolution of the proportion of contagious individuals in the total population of each region. Heterogeneity across regions reflects both differences in public health policies and testing/counting methods.

Once transmission rates are known, we identify its components in line with Eq. (9). The third component, $\left[(1 - \theta)\mu_{i,t}^a + \theta\mu_{i,t}^v\right]$, depends on the share of asymptomatic subjects among contagious individuals and on the fractions of infected workers who are still active on the labor market. Regarding the share of asymptomatic ($\theta$), the recent CON-VINCE Study (Snoeck et al., 2020) conducted on 1,862 Luxembourguish individuals identifies 35 cases with antibodies. These include 11 individuals who self-report to have been tested positive in the past months. This means that 1.3\% infected individuals (24 out of 1862) were undetected. Applying this percentage to the whole population gives a stock of asymptomatic of around 8,000, which is twice as large as the total stock of detected cases. Given the small number of people in the sample, the accuracy of these numbers is low. Our calibration assumes that $\theta = 0.5$.\textsuperscript{17}

The fractions of infected people who are active ($\mu_{i,t}^v, \mu_{i,t}^a$) depend on the efficiency and frequency of PCR testing. In the absence of testing, we assume that infected workers self-isolate when they show some symptoms. Asymptomatic people never self-isolate. Calculations presented in Section A.5 in the Appendix allow approximating the fraction of working days supplied by symptomatic and asymptomatic infected workers under several testing scenarios:

- In the absence of testing, we obtain $\mu_{i,t}^v = 0.20$ and $\mu_{i,t}^a = 1.0$ for all $t$.\textsuperscript{18}
- If a weekly test is performed, we have $\mu_{i,t}^v = 0.15$ and $\mu_{i,t}^a = 0.25$ for all $t$.
- If a daily test is performed, we have $\mu_{i,t}^v = \mu_{i,t}^a = 0$ for all $t$.
- If a one-shot test is performed at time $T$, we have $\mu_{i,T}^v = \mu_{i,T}^a = 0$, and we get back to $\mu_{i,t}^v = 0.21$ and $\mu_{i,t}^a = 1.0$ thereafter (i.e., for all $t > T$).

As massive testing was not implemented before and at the beginning of the lockdown, we have that $\left[(1 - \theta)\mu_{i,1}^v + \theta\mu_{i,1}^a\right] = \left[(1 - \theta)\mu_{i,0}^v + \theta\mu_{i,0}^a\right] = 0.6$. When simulating the deconfinement plan, we consider several testing scenarios.

Policy-related changes in transmission rates are captured by $\rho_{i,t}$. We normalize $\rho_{i,t}$ so that $\rho_{i,t} = \bar{\rho}_{i,t}e_{i,t}$ equals unity before the lockdown. This implies that $\bar{b}_{i} = b_{i,1}/0.6$ in each sector.

\textsuperscript{16}Note that the correlation between post-lockdown transmission rates with indices of exposure to risk is small (0.07), suggesting that lockdown measures were effective in reducing physical distance and exposure to disease.

\textsuperscript{17}Heneghan et al. (2020) cover 21 studies based on various contexts. The range of estimates of this proportion varies from 5\% to 80\%. In the case of the Diamond Princess cruise in which all individuals were tested, about 18\% were found to be asymptomatic. More recently, Fontanet et al. (2020) conduct a survey in a French high school involving pupils, teachers and non-teaching staff in the Oise region which was one of the first affected places of the epidemics in France. They find a rate of asymptomatic people of 17\% only, but argue that this is likely to underestimate the rate in the general population.

\textsuperscript{18}In the very first periods, the size of old infected cohorts is small or negligible (green cohorts in Figure A.3 in the Appendix), levels of $\mu_{i,t}^v$ around 0.3 or 0.4 are more likely to be observed.
and can be interpreted as a basic transmission rate. Then, the post-lockdown transmission rates are influenced by changes in presence rates at the workplace ($e_{i,t}$) and public health policies ($\rho_{i,t}$). As testing measures did not change during the first weeks of the pandemic, we set $\rho_{i,2}/\rho_{i,1}$ equal to $b_{i,2}/b_{i,1}$. We proceed similarly with the origin-specific transmission parameters. We normalize $\rho_{O,1}$ to unity so that $b_{0,1} = b_{O,1}$ in each region. Then, we set $\rho_{O,2}/\rho_{O,1}$ equal to $b_{O,2}/b_{O,1}$ and consider it as constant in the benchmark scenario.

Focusing on the 16 sectors with positive transmission rates, we find no correlation between $\rho_{i,1}/\rho_{i,2}$ and changes in the presence rate in the workplace, $e_{i,2}/e_{i,1}$. One might conclude that the decrease in $\rho_{i,t}$ is permanent and independent on the density of employees at the workplace, which means that restarting economic activities would only affect transmission rates through the extensive margin (i.e., $x = 0$ in Eq. (11)). Under this hypothesis, the decrease in transmission rates would then be entirely explained by permanent social distancing, hygiene and prevention measures. Transmission rates have decreased by 92 to 99% between the pre-lockdown and post-lockdown periods. This change seems too large to be induced by the extensive margin only. Some studies report that handwashing lower risks of respiratory infection, with risk reductions ranging from 6% to 44% (Rabbie and Curtis, 2006) and a mean effect around 25%. Studies on the effectiveness of masks and other infection breakers are more controversial. While Milton et al. (2013) argue that wearing surgical masks reduce influenza virus aerosols in human exhaled breath by 70%, there is ongoing debate whether masks can meet the expectations of respiratory protection devices (Oberg and Brosseau, 2008). The true effect lies somewhere between 0 and 70%. As for physical distancing, disentangling the permanent and lockdown-driven effects on infection rates is impossible. Jarvis et al. (2020) find that strict physical distancing interventions implemented in the UK reduce the reproduction number by about 70%. Combining the mean of these estimates and assuming these measures are permanent, transmission rates should have decreased by 70% only (as $0.30 = (1 - 0.25) \times (1 - 0.35) \times (1 - 0.35)$), while combining the upper bounds gives a 95% decrease (as $0.05 = (1 - 0.44) \times (1 - 0.7) \times (1 - 0.7)$).

It is rather unlikely that extensive-margin effects alone can explain the drop in transmission rates in all sectors. This implies that physical distancing measures are difficult to maintain when workers are massively brought back to work and employment goes back to its initial level. Inferring the size of the intensive-margin effect ($x$) from a small set of industry-specific observations is irrelevant. Hence, to account for uncertainty and for the possibility of a rebound in transmission rates, we thus compare several intensive-margin scenarios. We use three arbitrary values for the elasticity of transmission rates to the density of workers at the workplace: $x = (0.0, 0.2, 0.4)$. Once $x$ is chosen, $\overline{\rho}_{i,2}$ is calibrated to match $\rho_{i,2}$ and is assumed to be constant over time.

A last important parameter is the share of weekly social interactions that occur on the job, $\epsilon$. Fully employed workers spend about 40 hours at the workplace, out of a weekly total of 100 hours of interactions with family members, friends and non professional association mates. Assuming professional interactions involve twice more contacts than private contacts, we obtain a fraction $\epsilon = 0.7$ on-the-job, and a fraction $1 - \epsilon = 0.3$ in the place of residence. Note that the chosen value of $\epsilon$ also reflects the impact of additional interactions involved by the travel to the place of work, for instance using public transportation. The fraction $\epsilon$ is multiplied by the industry-specific employment rate at the workplace to account for the fact that unemployed people or teleworkers only have interactions in the place of residence.

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19 Individuals are instructed to stay at home and avoid leaving their house except for essential task. This translates into a 73% reduction in the average daily number of contacts per person.
Figure 2: Calibration of the SIIR model by sector

Note: Data on COVID-19 cases by sector (gray curve) are obtained from IGSS and aggregated by week (247 weekly obs.). Estimation of SIR model with 46 parameters are represented by the dashed black curve.
Figure 3: Epidemiological parameters.

Transmission Rates by Industry

Recovery Rates by Industry

Share of Infected by Region

Transmission Rates outside Labor Markets

Share of Infected by Region

Transmission Rates by Industry

Note: Authors' computations.
3 Results

We first estimate the trajectory of public health and economic indicators under a permanent lockdown hypothesis. Starting from that scenario, we then simulate the epidemiological and economic responses to various deconfinement measures. The gradual reopening of Luxembourg’s industries is examined in Section 3.2. In Section 3.3, we supplement the economic deconfinement scenario with a restart of leisure and social activities translating into greater transmission rates in the place of residence, in Luxembourg and in the rest of the Greater Region.

3.1 Effect of a permanent lockdown

The permanent lockdown hypothesis implies that the containment measures will not be lifted before the end of 2020. We also consider that the fall in exports and domestic demand is persistent, as illustrated in Figure 1. Although unrealistic (and already outdated), this worst-case economic scenario is used as a benchmark to evaluate the effect of deconfinement plans in the Section 3. In addition, in line with Fadinger and Schymik (2020) and Jones et al. (2020), the permanent lockdown hypothesis allows us to assess the crucial role that teleworking plays in mitigating the health and economic effects of the crisis as well as the role of exports.

In the pre-lockdown period, the macroeconomic effect is governed by the deterioration of the global economy in the first phase of the crisis. Then, when containment measures are implemented (March 20), the decline in output in lockdown industries and the decrease in final demand by domestic agents leads to complex cascading effects. Macroeconomic responses are presented in Figure 4. The top-left panel shows the weekly effect on the Luxembourg value added. In the first phase of the crisis, the deterioration of the global economy generates a decrease in weekly GDP that gradually converges to 3.0%. Then, on March 20, the lockdown translates into a disciplined and sizeable cut of about 28% compared to the pre-crisis level. This number is in line with the survey from the Chamber of Commerce and with the recent nowcasts described in STATEC (2020). Aggregating these effects over the entire year gives a decrease in annual GDP of around 22%. The bottom-left panel shows that the most adversely affected industries are ‘Construction’ (-66%), ‘Accommodation and Food’ (-62%), Mining and Quarrying (-43%), and ‘Wholeasale/retail trade and repair services’ (-42%). The least impacted industries are ‘Health and social work’ (-3%) and ‘Finance’ (-6%), ‘Education’ and ‘Public administration’ show limited responses around 10%.20

The top-right panel of Figure 4 shows the evolution of the proportion of infected people (in black) as well as the cumulative share of recovered people (in gray). Under the lockdown measures, the peak of the infection curves is observed during the first week of April with around 1,850 detected COVID-19 cases (we exclude asymptomatic people who were not detected as positive). The proportion of infected people reaches zero by mid-June, with a number of recovered people converging towards 4,400 individuals (i.e., 0.7% of the Luxembourg population). The bottom right panel represents the share of infected people by sector.21 Remember the number of asymptomatic cases is identical to that of symptomatic cases. Adding asymptomatic cases, the share of recovered people is around 1.4% of the

20This is due to the fact that the value added in this sector is measured by its cost of production. As teachers’ earnings have been paid normally, the value added is unchanged even if pupils are not in schools. In our model, we assume that teachers are equivalent to teleworkers in the period of school closures.

21Figure C.1 in the Appendix describes the health and economic implications of the lockdown measures for each industry.
population. This is obviously way below the collective immunization rate.

This result clearly suggests that the lockdown has drastically limited the propagation of the virus, which also implies that there is still a majority of susceptible workers in the Luxembourg labor force. For this reason, implementing an “almost risk-free” (in the sense that risk zero does not exist and isolation measures are not always respected) deconfinement strategy (Dewatripont et al., 2020), based on allowing only workers who test positive with a serological test and negative with a PCR test to return to work, is economically useless. Any economically meaningful strategy of deconfinement requires that non infected and non immune workers are gradually brought back to work, which induces a risk of a relapse.

We now investigate the role of teleworking and international trade during the lockdown period. Results are presented in Figure 5. The top panel focuses on the role of teleworking and assumes the absence of testing among teleworkers. The dashed gray curve shows the effect obtained when teleworking is not feasible. By moving teleworkers to unemployment, the cost of each week of lockdown increases from 28% in the benchmark to 51%. The effects on the infection curve are negligible as teleworkers spend all their time at home as the unemployed, and I/O multiplier effects are limited.

If teleworkers had worked from their workplace after the lockdown, labor productivity and weekly output levels would have been almost identical. The downside of this policy is that the infection curve would have shifted upwards and to the right. Remember that transmission rates depend on public policies and presence rates at the workplace (\(\rho_{i,t} = \bar{\rho}_{i,t,e} e_{i,t}^x\)). The top-right panel of Figure 5 simulates the infection curves under the three intensive-margin scenarios (i.e., \(x = (0, 0.2, 0.4)\)). When \(x = 0\), bringing back teleworkers to their workplace prevents the infection curve to fall to zero before the end of the year. This shows the importance of the extensive-margin effects of increasing employment and presence rates at the workplace. When \(x\) equals 0.2 or 0.4, increases the presence at the workplace affects the infection curve in the intensive margin. The infection curve shows a second peak at 1,500 or 2,600 detected cases, respectively. The cumulative number of cases reaches 11,000 with \(x = 0\), 15,200 with \(x = 0.2\), and 23,000 with \(x = 0.4\). In an economy such as Luxembourg, where skill-intensive services account for 75% of the GDP (finance services account for 45% alone), teleworkers accounts for more than 30% of the workforce. The role of teleworking has been instrumental to limiting the economic output loss and the propagation of the virus. We will show below that teleworking will play a key role as well in the deconfinement strategy.

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22 Dewatripont et al. (2020) argue that a prerequisite to bringing workers back to work is a reliable identification of individuals who will not contract the virus or transmit it to others. A combination of serological and PCR tests allows the detection of non infected and recovered individuals (the latter have been infected by the virus and have recovered). The authors argue: “As asymptomatic individuals who test positive with a serological test may still carry the virus and infect others for a certain period of time, there is a need to verify, through a PCR test, that these immune individuals are no longer carrying the virus. Only those who test positive with a serological test and negative with a RT-PCR test should be allowed to return to work.”

23 Yet, limited employment changes in the other sectors imply that the long-term number of recovered increases slightly (not shown here). Results available upon request.
Figure 4: Economic and public health effects of a permanent lockdown (worst-case economic scenario)

Note: Authors' simulations fitting the pre- and post-lockdown economic indicators as well as industry-specific data on detected Covid cases. Permanent lockdown and permanent disruption of the global economy.
Figure 5: Role of teleworking and exports during the lockdown.

Note: Authors’ computations. Permanent lockdown with alternative teleworking and trade scenarios.
The role of international trade has been less important, albeit non negligible. The bottom panel of Figure 5 compares our benchmark scenario, involving a permanent deterioration of the global economy, with two alternative scenarios. The light gray curve assumes that exports gradually get back to their initial level from the beginning of June to the end of the year ("Trade Optimistic"); the dark gray scenario assumes that trade recovery is halved ("Trade Neutral"). Trade disruption affected the economy in January and February, when production was driven by the demand side. In line with the economic impact found in January and February, the alternative trade scenarios have significant effects on economic variables, but negligible effects on the infection curve (very slight changes in infections are obtained due to rising employment). The economic cost of a week of lockdown decreases from 28% to 21% in the neutral scenario, while reaching 20% in the optimistic trade scenario. These effects are non negligible but remain relatively small in comparison with the effect of the lockdown itself, or with the effect of teleworking.

### 3.2 Gradual economic deconfinement: Hoping for the best

We now use the model to simulate a gradual economic deconfinement. Before considering a reopening of HORESCA (acronym for "hotels, restaurants, cafés") and a cessation of teleworking activities, our first deconfinement scenario combines four shocks:

- The first restarting stage started on April 20th and mainly involved the reopening of construction sites.
- Secondly, schools have gradually reopened since May 4. Reopening started with graduating classes in the secondary education, practical exercise classes and internships at University and for the Advanced Technician Certificates (BTS). Secondary schools reopened on May 11. Primary schools and public childcare services reopened on May 25.
- Other measures were implemented on March 11. These consist of removing constraints in all other sectors of the economy, with the exceptions of HORESCA as well as Arts, Entertainment and Recreative Services.
- To be consistent, we combine the deconfinement with the optimistic trade scenario involving a gradual recovery of exports from the beginning of June. We consider for the time being that teleworkers continue to work from home in the non-lockdown industries.

The public health and economics effects of these shocks are presented in Figure 6. The top panel compares the results obtained under the three intensive-margin scenarios ($x$ equal to 0.0, 0.2 and 0.4) and in the absence of on-the-job PCR testing. On the bottom panel, we focus on the pessimistic scenario with $x = 0.4$ and assess the effect of massive PCR testing policies. The economic effects of these shocks are almost identical across public health scenarios. The weekly costs of the lockdown gradually decrease from 27% to 23% when construction sites are reopened. Steeper effects are obtained after May 25, as many workers in parental leave are brought back to work in all industries when primary schools and public childcare services reopen. The weekly loss of output gradually decreases between April 20 and mid-June, and stabilizes at around 4% of GDP. Overall, the annual GDP of Luxembourg will decrease by 8% compared to normalcy in this scenario.

The epidemiological consequences of the deconfinement are highly sensitive to the intensive-margin scenario, as shown on the top-right panel of Figure 6. In the less pessimistic scenario (dashed dark and light gray curves corresponding to $x$ equal to 0.0 and 0.2), restarting all sectors has no effect on the aggregate infection curve. In the pessimistic scenario (dashed
light gray curve corresponding to $x = 0.4$), the effects are negligible until the beginning of June but then, the infection curve exhibits a strong rebound with a new peak at 1,500 detected COVID-19 cases (i.e., 3,000 cases if one includes asymptomatic cases) observed in the first week of December. The cumulative number of cases reaches 14,000 by the end of the year but the infection curve clearly suggests that this number will keep on rising in the course of 2021.

Although epidemiological effects are uncertain, two positive messages can be emphasized here. Firstly, massive PCR testing policies can be used to avoid a rebound in the infection curve, as illustrated on bottom-right panel of Figure 6. Starting from the pessimistic reproduction scenario ($x = 0.4$), on-the-job infection rates fall to zero and the global infection curve reaches zero at the very beginning of June under the weekly testing policy -- whose cost is likely to be prohibitive -- or under a monthly testing policy.

Secondly, the pessimistic scenario with $x = 0.4$ is unlikely to materialize. The economic deconfinement scenario involves the reopening of four sectors (Construction; Water, sewage and waste management; Real estate; Other services). Post-lockdown transmission rates in the last two sectors are very small, and the lockdown only partly affected the second sector. Hence, the epidemiological results in Figure 6 are mostly governed by the reopening of construction sites on April 20.24 This is illustrated in Figure 7 which depicts the evolution of the share of contagious workers by sector and by region of origin under the pessimistic scenario. The construction share starts to increase from early May and reaches around 2/3 of the total stock of contagious workers in September. Recent data on detected cases by sector do not evidence such a rebound in the construction sector. Consequently, we are relatively optimistic that the deconfinement measures implemented in April and May will not generate a relapse of the pandemic.

Can Luxembourg proceed a step further with its economic deconfinement? Excluding the pessimistic intensive-margin scenario with $x = 0.4$, we now simulate the effect of a further deconfinement scenario involving a restarting of the HORESCA sector from the beginning of June on, as well as a cessation of teleworking activities from the same date. The solid and dashed black curves in Figure 8 show the effect of a full reopening of HORESCA with $x$ equal to 0 or 0.2. The economic effects are similar: the effect on weekly GDP converges towards -1.5%, implying that the economy almost gets back to normalcy whatever the public health scenario.25 Overall, the annual GDP of Luxembourg will decrease by 7% compared to normalcy. The effect on the infection curve is negligible under $x = 0$, whereas a rebound is expected under $x = 0.2$. In the latter scenario, the epidemiological response is negligible until the beginning of July but then, the infection curve exhibits a strong rebound with a new peak at 1,000 detected COVID-19 cases (i.e., 2,000 cases if one includes asymptomatic cases) by mid-December.

Again, two positive messages can be emphasized here. Firstly, the bottom-right panel of Figure 8 shows that weekly or monthly testing can prevent that rebound. Secondly, the dashed light gray curve on the top-right panel shows that the infection curve converges toward zero under a partial restarting of HORESCA activities. Reopening restaurant at half of their capacity or with equivalent physical distancing measures appears to be a highly relevant and safe policy option.

24In section D, we show that very similar infection curves are obtained when simulating the reopening of the construction sector and the gradual reopening of schools only.

25The remaining loss is due to the closure of the recreative sector and its effects on the other sectors and the small fraction of positive COVID-19 cases.
Figure 6: Economic and public health effects of May 11 deconfinement measures

Note: Authors’ computations. We simulate here a restarting of all other sectors of the economy from May 11, with the exceptions of HORESCA as well as ‘Arts, Entertainment and Recreative Services’.
Figure 7: Shares of detected cases by sector and by origin

Pessimistic scenario: May 11 deconfinement measures with $x = 0.4$

Note: Authors’ computations. We simulate here a restarting of all other sectors of the economy from May 11, with the exceptions of HORESCA as well as 'Arts, Entertainment and Recreative Services'.
Figure 8: Deconfining HORESCA and bringing teleworkers back to their workplace from June 1

Note: Authors’ computations. We simulate here a restarting of HORESCA activities (in whole or in part) or a cessation of teleworking from June 1.
In contrast, bringing back teleworkers to their workplace induces larger epidemiological damages, even in the optimistic scenario with $x = 0$. Combined with the full restarting of HORESCA, the cessation of teleworking activities has limited effects on the weekly level of output, and drastic effects on the infection curves. A rebound in the infection curve occurs in the second half of July, with a number of detected COVID-19 cases peaking at 3,000 people (remember we do not count asymptomatic cases here, which would double the magnitude of the effect) by the end of September. This is entirely due to the extensive-margin effect of increased presence rates at the workplace. Adding the intensive-margin mechanism with $x = 0.2$, the rebound starts by the end of June with a number of detected COVID-19 cases peaking at 4,400 people in the beginning of September. Bringing back teleworkers to the office is not a relevant policy option, even if mitigation policies are implemented.

3.3 Resumption of social activities: Prepared for the worst

We now turn to a variant involving a full economic deconfinement and a resumption of social activities from the beginning of June. Physical distancing measures have drastically affected leisure, family and social life. Many daily interactions among family and friends have moved to messaging platforms. Most sport, culture and entertainment events have been cancelled. As the lockdown weeks turn into months, frustrations and impatience mount and people long for a return to a more normal social life. This last section investigates the effect of relaxing constraints on social activities outside the labor market.

In line with our intensive-margin scenarios – which link on-the-job transmission rates to the density of employees at the workplace – we allow transmission rates at the place of residence to partly return to their initial level once social life restarts. This might be due to restarting meals and parties with a limited number of friends and/or with family members, sport in small groups, more intensive use of public transportation, more contacts in shopping areas, mass departures during the holiday season or at weekends, etc. In all parts of the Greater Region (i.e., in Wallonia in Belgium, Grand-Est in France, Saarland and Rhineland-Palatinate in Germany), we have:

$$b^O_t = \chi b^O_1 + (1 - \chi) b^O_2,$$

where $\chi$ is a proxy for the fraction of permanent change in $\beta^O_t$. We use three arbitrary values for this fraction, $\chi = (1.0, .95, .90)$. Although the levels of $\chi$ are close to each other, these scenarios are very different. In the case of Luxembourg, we have $b^O_1 = 5$ and $b^O_2 = 0.25$ (similar patterns are observed in the other regions). Hence, compared with the post-lockdown level, $b^O_t$ is multiplied by 2 or 3 when $\chi$ equals 0.95 or 0.9, respectively.

In Figure 9, we combine the prudent and plausible scenario of economic deconfinement (i.e., $x = 0.2$) of Figure 8 with the three transmission scenarios outside the labor market (i.e., $\chi = (1.0, .95, .90)$). In the absence of on-the-job PCR testing, the pessimistic scenario of economic deconfinement involves a peak at 1,100 detected COVID-19 active cases in December. This corresponds to the black curve on Figure 9. Under the intermediate transmission scenario ($\chi = 0.95$), the number of detected COVID-19 active cases peaks at around 1,950 cases. Under the pessimistic scenarios ($\chi = 0.90$), the number of detected COVID-19 active cases skyrocket at around 10,500 detected cases.
Figure 9: Restarting social life in Luxembourg and in the Greater Region from May 11

Note: Authors’ computations. We start from the pessimistic scenario of economic deconfinement (i.e., $x = 0.2$) of Figure 8 and simulate a resumption of social activities under three reproduction scenarios outside the labor market ($X$ equal to 100%, 90% and 80%) in all parts of the Greater Region.
Two appeals for caution can be emphasized here. Firstly, our simulations evidence that future epidemiological trends are uncertain and highly sensitive to the capacity to sustaining physical distancing and hygiene constraints in social life. Secondly, though weekly and monthly testing can prevent a rebound when $\chi$ equals 1 or 0.95, the rebound looks inevitable under $\chi = 0.9$. This is illustrated on the bottom panel of Figure 9. Weekly testing on the job is not sufficient to prevent the relapse as people get infected outside the labor market. In the pessimistic scenario with $\chi = 0.9$, daily PCR tests, whose cost is prohibitive, would be required to prevent the relapse.

4 Policy implications

Our model jointly endogenizes the health and economic responses to the COVID-19 crisis and the related containment and public health policy measures implemented in Luxembourg and in the Greater Region. It allows us to quantify the economic and public health effects of the lockdown as well as the response to gradual deconfinement measures under various economic, epidemiological and public health scenarios.

As a result from physical distancing, hygiene and prevention measures, transmission rates decreased drastically in Luxembourg and in the Greater Region between the pre- and post-lockdown periods. If post-lockdown transmission rates could be kept constant throughout the whole deconfinement phase, restarting all sectors would have huge effects on the economy and no effect on the aggregate infection curve. In that sense, it is a good time for lifting containment measures. Nevertheless, there is huge uncertainty regarding the share of the drop in transmission rates that can be considered as permanent both in and outside the labor market. Epidemiological results are sensitive to the evolution of this share.

Given the trends observed during recent weeks, we are relatively optimistic that the economic deconfinement measures implemented in April and May will not generate a relapse of the pandemic. However, the resumption of social life and, to a lesser extent, the reopening of HORESCA activities generate more uncertain effects on the infection curve. As policymakers must be prepared to face critical situations, three precautionary measures can be drawn from our analysis:

• **R1** – Maintaining teleworking practices is vital. All of our simulation results indicate that a cessation of teleworking practices would induce large epidemiological damages, even if drastic mitigation policies were implemented. In the model’s terms, maintaining teleworking practices ensures that the infection curves converge towards zero after the economic deconfinement measures of April and May under the conservative intensive-margin scenario with $x = 0.2$.

• **R2** – Reopening HORESCA activities at half of their full capacity or with appropriate physical distancing measures generates very small effects on the infection curve and appears to be a very relevant policy option. Such a partial reopening ensures that the infection curves converges towards zero under the conservative intensive-margin scenario with $x = 0.2$.

• **R3** – Our results also indicate that the evolution of the number of COVID-19 cases is highly sensitive to reproduction numbers outside the labor market. Maintaining hygiene measures and high levels of physical distancing in social life has an important impact on the number of COVID-19 cases. In the model’s terms, physical distancing in social life must be such that $b^O$ cannot be more than two times larger than the post-lockdown level, $b^O_2$ in all regions of origin $O$. 

30
Yet, in the absence of tracing or testing measures, a rebound in the infection curve is likely if the resumption of social life is such that $b^0_t$ approaches $2 \times b^2_0$, and/or if HORESCA activities restart without sufficient physical distancing measures. We consider such a worst-case scenario in which $x = 0.2$, $\chi = 0.95$, and all economic activities are restarted (including HORESCA services at their pre-lockdown level). This scenario is illustrated on the top-right panel of Figure 10. Without testing (solid black curve), the infection curve remains stable between the end of May and mid-August, at which time a rebound in the infection curve is observed, leading to a second peak at around 1,900 detected people by mid-December. A weekly testing policy suffices to isolate contagious workers and prevent that rebound. The cost of such weekly tests is likely to be prohibitive. On the contrary, a ‘one-shot massive testing’ policy only postpones the no-testing outcomes by two weeks.\footnote{Considering that the full capacity of ICU services is around 90 beds and 1/20 symptomatic COVID-19 cases need ICU health cares, the infection curves should be stabilized below 1,800 COVID-19 cases. We also simulated an ‘On-Demand testing’ policy, which assumes repeated massive testing each time the number of cases reaches 1,800. This requires a new PCR massive testing wave in the beginning of December.}

In this worst-case scenario, it is reassuring that monthly PCR tests can be used to prevent the rebound. Compared to weekly tests, monthly testing slightly reduces the speed at which the infection converges towards zero. However, to be fully effective, it is important to emphasize that all workers, nationals and cross-border commuters, should be tested at the same frequency. On the bottom panel of Figure 10, we show that restricting the same tests to nationals only is not enough to prevent a slow and gradual rebound in the infection curve.

Hence, two additional recommendations can be drawn from our analysis:

- **R4** – Monthly PCR testing of national and cross-border workers are sufficient (perhaps not necessary) to prevent a rebound in the infection curve.
- **R5** – Combining testing with contact tracing would reduce transmission rate below further. Ferretti et al. (2020) show that tracing pre/a-symptomatic people with a phone app and quarantining contacts of new detected cases would reduce the transmission rate by up to 50%. This roughly corresponds to the effect of weekly tests, but it is more effective than our monthly testing policy. In our setting, combining testing with contact tracing would allow reducing the required frequency of testing (e.g., a test every two of three months is likely to be sufficient).

Our five recommendations are dependent on the pessimistic reproduction scenarios considered in quantitative exercises. The testing and accompanying measures might need to be tightened if infection rates are increasing more rapidly until a vaccine is widely available. Alternatively, they might be relaxed if a higher fraction of recent distancing and prevention behaviors prove to be permanent and sustainable. We see our accompanying measures as safe and prudent recommendations in the direct aftermath of the deconfinement phase.
Figure 10: Alternative testing policies

Note: Authors' computations.
References


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A Architecture of the epidemiological block

In line with the time structure of our economic block, our epidemiological block formalizes the dynamics of the stocks of susceptible \((L_{i,S}^t)\), infected \((L_{i,I}^t)\) and recovered \((L_{i,R}^t)\) workers in industry \(i\) over periods of one week \((t = 1, ..., T)\). Traditional SIR models have a daily interpretation \((\tau = 1, ..., \Upsilon)\) and assume a closed system implying constant population \((L_i = L_{i,S}^\tau + L_{i,I}^\tau + L_{i,R}^\tau \ \forall \tau)\) and no contamination by outsiders. Starting from a standard SIR model, this Appendix discusses the steps that lead to our weekly epidemiological model with dynamic recovery rates, inter-industry linkages and contamination by outsiders.

A.1 Dynamic vs probabilistic recovery rates

Discretization of the standard daily SIR system gives:

\[
\begin{aligned}
L_{i,S}^{\tau+1} &= L_{i,S}^\tau - \beta_{i,\tau} L_{i,S}^\tau L_{i,I}^\tau - L_{i,I}^\tau \left(1 - \beta_{i,\tau} L_{i,I}^\tau\right) \\
L_{i,I}^{\tau+1} &= L_{i,I}^\tau \left(1 - \gamma_{i,\tau}\right) + \beta_{i,\tau} L_{i,S}^\tau L_{i,I}^\tau - L_{i,I}^\tau \left(1 - \gamma_{i,\tau} + \beta_{i,\tau} L_{i,I}^\tau\right) \\
L_{i,R}^{\tau+1} &= L_{i,R}^\tau + \gamma_{i,\tau} L_{i,I}^\tau
\end{aligned}
\]

(13)

where \(\tau\) is the daily time index, \(\beta_{i,\tau}\) and \(\gamma_{i,\tau}\) are interpreted as the daily transmission and recovery rates in industry \(i\) at time \(\tau\).

The daily transmission rate, \(\beta_{i,\tau}\), can be influenced by industry-specific characteristics (physical proximity, number of contacts, exposure to disease) and by public health policies (physical distancing, hygiene and prevention measures, etc.). Hence, it must be treated as an endogenous and time-varying rate.

As for the recovery rate, it is usually perceived as a biological and disease-specific parameter that is linked to the average duration of infectious period. In the case of COVID-19, the length of the contagion period is about 10 days, implying that the average daily recovery rate is usually expressed as one over ten days \((\gamma_{i,\tau} = 0.1 \ \forall i, \tau)\). This value is relevant in two particular situations:

- In a deterministic case where contagious people recover after 10 days, \(\gamma = 0.1\) is relevant if the total stock of infected people at time \(\tau\) is uniformly distributed over the 10 infected daily cohorts (whose sizes are given by \(\beta_{i,\tau-k} L_{i,S}^\tau L_{i,I}^{\tau-k} \ \forall k = 0, ..., 9\)).
- In a probabilistic setting, \(\gamma = 0.1\) is relevant if each infected individual has a constant daily probability to recover regardless of when she became infectious.

Apart from these situations, the number of healings varies along the life cycle of the disease. In the (arguably most relevant) deterministic case where the length of the contagion period is

\[35\]

\[27\]This is illustrated in Figure A.3 where each pair of vertical bars represents a cohort of infected people. Each bar spreads over 10 contagion days. The plain-color area is meant to represent the asymptomatic period (i.e., 2/10 days for symptomatic cases and 10/10 days for asymptomatic cases). The stock of infected people at day \(\tau\) (or at day \(\tau + 7\)) is surrounded by the thick-border box in gray (or on black). On average, infected people at time \(\tau\) will remain contagious during 4.5 days after day \(\tau\) (0 day for cohort \(\tau - 9\), 1 day for cohort \(\tau - 8\), ..., and 9 days for cohort \(\tau\)).
assumed to be exactly equal to 10 days, the number of healings at day $\tau$ is equal to the number of people who became contagious at day $\tau - 9$. This number is given by $\beta_{i,t-9}\frac{L^S_{i-9}L^I_{i-9}}{L_i}$. In this setting, system (13) must be rewritten as:

$$
\begin{align*}
L^S_{i,\tau+1} &= L^S_{i,\tau} - \beta_{i,t}\frac{L^S_{\tau}L^I_{\tau}}{L_i}, \\
L^I_{i,\tau+1} &= L^I_{i,\tau} + \beta_{i,t}\frac{L^S_{\tau}L^I_{\tau}}{L_i} - \beta_{i,t-9}\frac{L^S_{\tau-9}L^I_{\tau-9}}{L_i}, \\
L^R_{\tau+1} &= L^R_{\tau} + \beta_{i,t-9}\frac{L^S_{\tau-9}L^I_{\tau-9}}{L_i}.
\end{align*}
$$

(14)

A numerical example allows to illustrate the implication of approximating system (14) using system (13). Consider a closed system with 1,000 people starting at time 1 with 999 susceptible and 1 infected individuals (and $L^I_{1,\tau} = 0 \ \forall \tau < 1$). The initial transmission rate is equal to 0.2 and people fully recover after 10 days. This implies that without prevention measures, there would be 226 susceptible, 2 infected and 772 recovered individuals after 365 days. However, at day 22 (beginning of fourth week), the transmission rate falls to 0.15 due to an exogenous intervention. This implies that there will be 440 susceptible, 2 infected and 558 recovered individuals after 365 days. We introduce this change in $\beta_{i,t}$ to examine whether it can be accurately identified by the system. The continuous curve in Figure A.1a shows the evolution of the stocks of susceptible, infected and recovered individuals over the first 14 weeks.

Figure A.1b shows the evolution of the ratio of daily healings to the stock of contagious individuals, the true measure of $\gamma_{i,\tau}$. These curves start from 0 at the beginning of the epidemic (days 1 to 9), as the very first infected individual needs 10 days to recover. Then, it becomes positive but smaller than 0.1 (denoted by $\gamma_0$ henceforth and represented in dashed gray) at the beginning of the epidemic (until day 31). This is because earlier infected cohorts are smaller in size than the most recent ones. The shock in the transmission rate on day 22 translates into a decrease in the recovery rate 10 days later. Then $\gamma_{i,\tau}$ increases again and at the end of the epidemic, it is larger than $\gamma_0$. This is because earlier infected cohorts are greater in size than the most recent ones.

The fact that the true fraction $\gamma_{i,\tau}$ varies over the life cycle of the epidemic has important implications for the estimation of the SIR model. Many SIR models are used to identify the dynamics of transmission rates ($\beta_{i,\tau}$) that fit the dynamics of the share of infected people ($L^I_{1,\tau}$) assuming a constant level for $\gamma$ (say $\gamma_0 = 0.1$), and then use projections of $\beta_{i,\tau}$ to predict the future share of infected people. By imposing a constant $\gamma_0$ which is greater than the actual recovery rate at the beginning of the epidemic, the calibrated level of $\beta_{0,\tau}$ is greater than its actual value. The opposite pattern ($\beta_{0,\tau} < \beta_{i,\tau}$) emerges after the peak of the infection curve.

Figure A.1c illustrates the biases ($\beta_{0,\tau} - \beta_{i,\tau}$) implied by the hypothesis of a constant $\gamma_0$. The true value of $\beta$ is represented by the continuous black curve. First, deviations from the true value are large. If one uses $\beta_{0,\tau}$ to forecast the number of infected people, projections errors might be important. Second, $\beta_{0,\tau}$ exhibits more gradual changes that are not compatible with the one-shot decrease in the true $\beta_{i,\tau}$. Third, a constant $\gamma_0$ leads to an overestimation of the change in transmission rates between the initial and final phases of the epidemic. Fourth, although the identification of $\beta_{0,\tau}$ is such that the model replicates the trajectory of $L^I_{i,\tau}$, another implication of misestimating $\beta_{i,\tau}$ and $\gamma_{i,\tau}$ is that the model wrongly predicts the long-run levels of $L^S_{i,\tau}$ (by -10.2%) and $L^R_{i,\tau}$ (by +7.8%). This is illustrated in Figure A.1a, where the true trajectory of these variables (continuous curves) is compared with predicted
values (dashed curves). It is worth noticing that smoothing $\hat{\beta}_{i,\tau}$ does not attenuate the biases. In contrast, calibrating system (13) allows to retrieve the true parameters. This is the reason why we opt for a dynamic (rather than for a “probabilistic”) recovery process.

### A.2 From a daily to a weekly structure

Starting from the daily system with a dynamic recovery process, the evolution of the stocks of susceptible, infected and recovered across weeks is governed by:

$$
\begin{align}
L_{i,\tau+7}^S &= L_{i,\tau}^S - \sum_{k=0}^{6} \beta_{i,\tau+k} \frac{L_{i,\tau+k}^S}{L_i} L_{i,\tau+k}^I \\
L_{i,\tau+7}^I &= L_{i,\tau}^I + \sum_{k=0}^{6} \beta_{i,\tau+k} \frac{L_{i,\tau+k}^S}{L_i} L_{i,\tau+k}^I - \sum_{k=0}^{6} \beta_{i,\tau+k-9} \frac{L_{i,\tau+k-9}^S}{L_i} L_{i,\tau+k-9}^I \\
L_{i,\tau+7}^R &= L_{i,\tau}^R + \sum_{k=0}^{6} \beta_{i,\tau+k} \frac{L_{i,\tau+k}^S}{L_i} L_{i,\tau+k}^I - \sum_{k=0}^{6} \beta_{i,\tau+k-9} \frac{L_{i,\tau+k-9}^S}{L_i} L_{i,\tau+k-9}^I 
\end{align}
$$

(15)

Changing time notations such that $t$ now represents weeks (and not days) and starting from the same day ($t = \tau$), our weekly system can be expressed in its reduced form as:

$$
\begin{align}
L_{i,t+1}^S &= L_{i,t}^S - b_{i,t} \frac{L_{i,t}^S}{L_i} L_{i,t}^I \\
L_{i,t+1}^I &= L_{i,t}^I + b_{i,t} \frac{L_{i,t}^S}{L_i} L_{i,t}^I - G_{i,t}^R \\
L_{i,t+1}^R &= L_{i,t}^R + G_{i,t}^R 
\end{align}
$$

(16)

where $b_{i,t} = \sum_{k=0}^{6} \beta_{i,\tau+k} \frac{L_{i,\tau+k}^S}{L_i} L_{i,\tau+k}^I$ is interpreted as the weekly transmission rate and $G_{i,t}^R = \sum_{k=0}^{6} \beta_{i,\tau+k-9} \frac{L_{i,\tau+k-9}^S}{L_i} L_{i,\tau+k-9}^I$ is the weekly flow of recovered.

As approximation, we assume a uniform distribution of new infections within a week. This does not imply that the total stock of infected people, $L_{i,\tau+k}^I$, is uniformly distributed over the 10 infected cohorts at time $t$, an assumption that would allow to use a constant recovery rate (see previous section). This means that $L_{i,\tau+k}^I$ increases by the same number at each day of the week or, equivalently, that the slope of the infection curve is constant within a week. It writes as:

$$
\beta_{i,\tau+k} \frac{L_{i,\tau+k}^S}{L_i} L_{i,\tau+k}^I \approx \beta_{i,\tau} \frac{L_{i,\tau}^S}{L_i} L_{i,\tau}^I \forall k = 0, ..., 6.
$$

(17)

This assumption implies that (i) the weekly flow of new contagion is seven times larger than the daily flow, (ii) that the weekly transmission rate is seven times larger than the daily transmission rate, $b_{i,t} = 7 \beta_{i,\tau}$, and (iii) that the weekly flow of recovered can be approximated by

$$
G_{i,t}^R = \frac{2}{7} b_{i,t-2} \frac{L_{i,t-2}^S}{L_i} L_{i,t-2}^I + \frac{5}{7} b_{i,t-1} \frac{L_{i,t-1}^S}{L_i} L_{i,t-1}^I.
$$

(18)

This is illustrated in Figure A.3. The stock of contagious people at the beginning of time $t + 1$ (box surrounded by the thick black border) is equal to the stock of contagious people at the beginning of time $t + 1$ (box surrounded by the thick gray border, including cohorts colored in red and in green), minus the recovered (cohorts colored in green), plus the weekly flow of new infections (cohorts colored in yellow). The weekly flow of recovered comprises two of the seven cohorts that were infected during week $t - 2$ (i.e., the first term in Eq. (18)) as well as five of the seven cohorts that were infected during week $t - 1$ (i.e., the second term...
in Eq. (18)). The recovery rate in week $t$ can be expressed as $g_{t,t} = G_{t,t}^R / L_{t,t}^I$. 

38
Is this assumption of a constant slope of the within-week infection curve more satisfactory than the assumption of a constant $\gamma_0$ in the probabilistic model? The answer is definitely affirmative. Starting from the numerical example of the previous section and gathering data on the number of infected people at the beginning of each week, we recursively compute the weekly flow of new infections, the weekly flow of recovered (equal to lagged infection flows as defined in Eq. (18)), and identify the parameters $b_{i,t}$ and $g_{i,t}$ that perfectly fit the infection curve. We then simulate the evolution of the number of susceptible and recovered. Figure A.2a shows that the simulated numbers (thin curves with diamonds) almost perfectly correspond to the true numbers (solid thick curves).

Figure A.2: Weekly model with dynamic recovery process

(a) Dynamics of SIR stocks over the first 14 weeks

(b) Estimation of the weekly transmission rate ($b_{i,t}$)

As for the identification of $b_{i,t}$ and $g_{i,t}$, their evolution is depicted in Figure A.2b. The $g_{i,t}$
curve resembles that of the daily model (after some rescaling). The $b_{i,t}$ curve shows a big drop between week 3 and week 4, in line with the transmission shock. As $b_{i,t}$ is an average of seven days, this shock is smoothed over a few periods. Fitting this curve with two parameters, one pre-shock level and one post-shock level, would give a very good fit.

A.3 Adding contamination by outsiders

Another feature of our model is that susceptible individuals in industry $i$ can be contaminated by infected people outside the labor market (in family or in social life). Virus transmission is now a weighted sum the transmission rates on the job (with weight $\kappa_{i,t}$) and outside the labor market (with weight $1 - \kappa_{i,t}$). Hence, system (16) becomes:

$$
\begin{align*}
L_{S,i,t+1} &= L_{S,i,t} - \kappa_{i,t}b_{i,t}L_{S,i,t}L_{I,i,t} - (1 - \kappa_{i,t})b_{0,t}L_{I,i,t}p_t \\
L_{I,i,t+1} &= L_{I,i,t} + \kappa_{i,t}b_{i,t}L_{S,i,t}L_{I,i,t} + (1 - \kappa_{i,t})b_{0,t}L_{I,i,t}p_t - G_{R,i,t} \\
L_{R,i,t+1} &= L_{R,i,t} + G_{R,i,t}
\end{align*}
$$

(19)

where $\kappa_{i,t}$ denotes the time spent on the labor market by workers from industry $i$ at time $t$, $b_{0,t}$ is the weekly transmission rate outside the labor market, and $p_t$ is the proportion of infected people in the total population. The weekly flows of recovered within group $i$ must be rewritten as:

$$
G_{R,i,t} = \frac{2}{7} \left[ \kappa_{i,t-2}b_{i,t-2}L_{S,i,t-2}L_{I,i,t-2} \right] + (1 - \kappa_{i,t-2})b_{0,t-2}L_{I,i,t-2}p_{t-2} + \frac{5}{7} \left[ \kappa_{i,t-1}b_{i,t-1}L_{S,i,t-1}L_{I,i,t-1} \right] + (1 - \kappa_{i,t-1})b_{0,t-1}L_{I,i,t-1}p_{t-1}.
$$

(20)

If $p_t$ always remains positive, the only steady state of this economy involves $L_{R,i} = L_i$. However, $p_t$ is linked to the average proportion of infected across all groups and might converge to zero. This implies that this extended SIR model has similar properties as the standard one.

A.4 Endogenizing virus transmission

The link between the economic and epidemiological blocks of the model operates through $\chi_{i,t}$. Weighted transmission rates are influenced by economic conditions, by industry-specific characteristics, and by public health measures. For a given proportion of susceptible and infected workers in industry $i$, on-the-job virus transmission depends on the share of daily interactions/contacts experienced on the labor market (1), on the average number of contacts per person per unit of time (2), and on the probability that infected people can have contacts with susceptible subjects (3). We express it as:

$$
\kappa_{i,t}b_{i,t} = \left(1 - \theta\right)\mu_{i,t}^w + \theta\mu_{i,t}^n
$$

(21)
where $\epsilon e_{i,t}$ the interaction time spent on the job (product of the average fraction of time spent on the labor market by the fraction of time spent in daily social interactions on the job); this is meant to represent effect (1). As for effect (2), it is the product of $b_i$, an industry-specific parameter that reflects working conditions in normal times (physical proximity and exposure to disease), by $\rho_{i,t}$. the latter is a variable capturing prevention and physical distancing measures implemented in the industry. Effect (3) is expressed as $[(1 - \theta)\mu^v_{i,t} + \theta \mu^a_{i,t}]$, which captures the probability that a contagious worker goes to work at time $t$.

If $\rho_{i,t}$ depends on the density of workers at the workplace (proxied by $e_{i,t}$), changes in employment rates influence transmission rates through the extensive margin – changes in time spent on the job – and the intensive margin – physical distancing on the job. A potential specification is $\rho_{i,t} = \rho_{t} e_{i,t}$ where $x$ is the elasticity of physical distancing to the presence of workers at the workplace. If $x = 0$, a lockdown-driven decrease in $\rho_{i,t}$ is permanent; if $x > 0$, part of that decrease is lost when workers get back to their workplace.

Similarly, transmission rates outside the labor market can be expressed as:

$$
(1 - \kappa_t) b_{0,t} = (1 - \epsilon e_{i,t}) \bar{b}_0 \rho_{0,t}
$$

(22)

where $1 - \epsilon e_{i,t}$ is the interaction time spent outside the labor market (one minus interaction time spent on the job), $\bar{b}_0$ is a region-specific parameter that reflects living conditions, $\rho_{0,t}$ is a variable capturing prevention and physical distancing measures implemented outside the labor market.

### A.5 Timing of the epidemiological process

To approximate the parameters governing the effectiveness of testing policies, we count the number of working days supplied by all infected cohorts during the first six days of week $t$ (i.e. from day $\tau$ to $\tau + 6$) ignoring the relative size of the different cohorts. Figure A.3 shows that 15 cohorts can supply labor during week $t$. Each cohort is represented by a vertical bar whose length corresponds to 10 infectious days. Members of the green, red and yellow cohorts can supply a maximum of 27, 18 and 15 days, respectively. This means a maximum of 60 working days. We assume new infected people are asymptomatic during at least 2 days, represented in light green, red or yellow. Then, symptomatic people show symptoms during 8 additional days, represented in dashed color. Asymptomatic people never show symptoms.

If no testing is done during week $t$, we can count the share of working days (excluding $\tau + 7$) that symptomatic workers from cohort $t - 1$ spend on the labor market without symptoms: this gives 0 days for the green cohorts, 3 days for the red ones, and 9 days for the yellow ones. This represents a total of 12 days out of 60. Hence, $\mu^v_{it} = 0.20$. As for asymptomatic people, $\mu^a_{it} = 1.00$.

If a weekly test is performed (say on Monday 8AM) and results are known immediately (Or equivalently, the test can be performed on Sunday at 8PM and results are known on Monday morning), the only workers supplying working days are those of the yellow cohorts, with 9 days for the symptomatic and 15 for the asymptomatic. We thus have $\mu^v_{it} = 0.15$ and $\mu^a_{it} = 0.25$.

Finally, in case a daily test is done at 8AM with immediate results, we have $\mu^v_{it} = \mu^a_{it} = 0$. 
Figure A.3: Adjustment of epidemiological parameters to the weekly time structure

Note: Each daily cohort of new infected people is represented as a horizontal bar.
Validation of our calibrated transmission rates

Heterogeneity in transmission rates across industries is supposed to reflect differences in exposure to risk. To validate our calibration strategy, we correlate our $b_{i,t}^{lab}$ with an index of exposure to risk. We use data on the need of physical proximity to operate ($ER_{1,i}$) and on workers’ exposure to diseases ($ER_{2,i}$). Occupation-specific proximity indices can be computed using the O’Net database, and aggregated by industry using the occupational shares in employment. Disease exposure indices can also be computed using the industry shares of workers heavily occupied in medical occupations and health services reported in the same O’Net database. To construct an index of exposition to risks for each industry $i$ ($ER_i$), we standardize each risk factor $ER_{k,i}$ so that the maximal value equals 100, and combine them using a risk technology that gives greater weights to larger values:

$$ER_i = \left[ \frac{\sum_k ER_{1+k,i}^{1+\xi}}{K} \right]^{1/(1+\xi)},$$

where $\xi \geq 0$ is a parameter penalizing large values (if $\xi = 0$, $ER_i$ is the arithmetic mean of $ER_{k,i}$), $K$ is the number of risk indicators (only 2 in our case).

Results are depicted in the last column of Table B.1 for $\xi = 4$. The minimal exposition to risk is obtained for ‘Agriculture, forestry and Fishing’, whereas the maximal level is obtained in the ‘Health and social work’ sector, followed by ‘Accommodation and Food’, and ‘Education’. Then, Figure B.1 shows the correlation between the basic reproduction numbers and the exposure to risk across industries.

Figure B.1: Correlation between basic transmission rates and indices of exposure to risk

Note: Authors’ computations. On the vertical axis, $b_{i,1}$ is our proxy for the basic transmission rates by industry at the early stage of the Covid-19 crisis.

See [http://www.onetcenter.org/](http://www.onetcenter.org/)
### Table B.1: Epidemiological parameters

<table>
<thead>
<tr>
<th></th>
<th>Proximity</th>
<th>ProxMax</th>
<th>Exp disease</th>
<th>ExpMax</th>
<th>Index</th>
</tr>
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<tbody>
<tr>
<td>Agric., forestry, fishing</td>
<td>30.6</td>
<td>0.430</td>
<td>4.9</td>
<td>0.181</td>
<td>0.395</td>
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<td>Mining, quarrying</td>
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<td>Manufactured products</td>
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<td>0.730</td>
<td>1.2</td>
<td>0.0444</td>
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<tr>
<td>Electricity, gas, steam</td>
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<td>1.3</td>
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<td>Water, sewageage, waste</td>
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<td>0.621</td>
<td>13.7</td>
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<tr>
<td>Construction</td>
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<td>1</td>
<td>0.037</td>
<td>0.783</td>
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<tr>
<td>Wholesale, retail, repair</td>
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<td>0.871</td>
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</tr>
<tr>
<td>Transport., storage</td>
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<td>0.663</td>
<td>4.2</td>
<td>0.156</td>
<td>0.610</td>
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<td>Accommodation, food</td>
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<td>Information, comm.</td>
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<td>Adminis., support</td>
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<td>Public administration</td>
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<td>12.4</td>
<td>0.459</td>
<td>0.536</td>
</tr>
</tbody>
</table>

Source: Authors’ computations based on O’Net data on physical proximity between workers and exposure to diseases by profession, and SILC data on occupational shares by industry.

## C Cost of the lockdown by sector

Figure C.1 describes the health and economic implications of the lockdown measures for each industry. Aggregate effects are presented in the core of the text (see Figure 4).
Figure C.1: Economic and public health effects of a permanent lockdown by sector

Note: Authors’ computations. Permanent lockdown and permanent disruption of the global economy.
D Reopening construction sites and schools

The first restarting stage, which started on April 20th, mainly involved the reopening of construction sites. In addition, schools have partly reopened since May 4. The reopening started with graduating classes in the secondary education, practical exercise classes and internships at University and for the Advanced Technician Certificates (BTS). In a second stage starting on May 11, secondary schools have been reopen. In the third stage starting on May 25, primary schools have been reopen and public childcare services have been organized. Teachers (considered as teleworkers during the lockdown) gradually get back to their workplace and have interactions with pupils. Public teachers represent around 22.2% of public administration; 58.6% percent of public teachers work in the secondary education and 41.4% percent in primary schools. In the first stage, only a fraction of secondary school teachers return to work (5.2% of teaching staff in private education, representing 1.2% of public administration). In the second stage, the remaining secondary teachers return to school which translates in an additional return of 36.2% of private education workers and 8% of public administration workers. In the third stage, 58.6% of primary private education workers and 13% of private education workers return to teach in class.

We simulate the effects of these shocks under alternative reproduction and testing scenarios. To be consistent, we combine the reopening of construction sites and schools with the intermediate (half-recovery) trade scenario described in Section 2.3. Hence, we jointly capture the effect of the first restarting stage and the partial recovery of exports. Results are presented in Figure D.2 assuming that nothing else happens until the end of the year. The economic effects of these shocks are strongly robust to the public health policy. The weekly costs of the lockdown gradually decrease from 27% to 23% when construction sites are reopened. Reopening schools mostly impacts the economy through its effect on parental leave. Parental leave has been broadly lifted with the final stage of school reopening on May 25, remaining available to parents in a few exceptional cases only. We therefore assume that only 10% of workers that benefit from parental leave are remaining in this status after May 25. Gradual economic gains due to the partial recovery in exports and decrease in parental leave are observed. By the end of the year, the weekly output loss lies in the vicinity of 12% (i.e., 15 percentage points smaller than during the full lockdown).

Turning to the epidemiological consequences of these shocks, the top-right panel of Figure D.2 compares the results obtained under the three intensive-margin scenarios (x equal to 0, 0.2 and 0.4) and in the absence of on-the-job PCR testing. In the least pessimistic scenarios (dashed dark and light gray curves corresponding to x = 0 and x = 0.2), restarting the construction industry and reopening schools has no effect on the aggregate infection curve. In the pessimistic scenario (solid black curve corresponding to x = 0.4), a rebound in the infection curve is observed, with a new peak at 1,600 detected active COVID-19 cases during the third week of December. Note that the rebound is negligible until the end of May but then, the infection curve exhibits a strong rebound. Hence, in the absence of massive testing, epidemiological results are sensitive to the size of the intensive margin effect of employment. However, mitigation policies can be used to avoid a relapse. On the bottom-right panel of Figure D.2, we focus on the pessimistic scenario and consider two testing strategies, which consists of testing workers on a weekly or monthly basis. Testing workers on a monthly basis suffices to avoid the rebound.

29 The distribution between primary and secondary classes is assumed to also hold in the private education sector, for which we do not have this detailed information.
Figure D.2: Economic and public health effects of reopening construction sites by April 20

Note: Authors’ computations.