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Abstract

Using a standard labor choice model I show how economic activity shapes and—at the same time—is shaped by an epidemic. Then, I use this framework to validate with a montecarlo analysis the stage-based identification strategy of policy effects recently proposed in Aleman et al. (2020a). I then describe their assessment of the effectiveness of the Spanish stay-home policy against Covid-19.

1 Introduction

In light of the Covid-19 pandemic, many economists (among other social scientists) have grown interested in understanding contagion through endogenous economic and health behavior (see Atkeson, 2020). The idea is that economic activity—through human contact interaction—inevitably entails contagion risk. This risk derived from economic activity occurs through different settings including contagion at work (Houstecka et al., 2021), social activities (Toxvaerd, 2020) and home (also nursing homes) (Brotherhood et al., 2020). Since contagion can result in sickness and death, an epidemic poses a trade-off between economic activity and public health policies that aim to deter contagion at the cost of reducing economic activity (e.g. Adda, 2016; Barro et al., 2020). Therefore, in order to quantitatively assess the trade-off between economic activity and public health policy, it is essential to accurately measure the effectiveness of public health policy against the spread of an epidemic.[1] In this note I provide a brief summary of the work

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[1] The study of disease spread and the effects of public health policy is not new. In particular, epidemiologists provide extremely detailed models of disease spread, often with many different factors linked to what a person is

in Aleman et al. (2020a) in which we propose a stage-based identification of policy effects.[2] In particular, I highlight one of the applications in that paper that assesses the effectiveness of the nationwide stay-home policy implemented against Covid-19 in Spain.

2 Economic Activity and Public Health

To illustrate the trade-off by which economic activity shapes and—at the same time—is shaped by public health in the context of Covid-19, consider a 2-period economy with labor choice that faces a contagious virus. In the first period, a one-household economy is born with a mass $N = 1$ of identical healthy agents. During the first period, some of these agents get infected—due to economic activity—and a proportion of the infected do not survive to the second period. That is, economic activity—through the amount of hours worked—shapes the epidemic by lowering the survival rate to the second period. At the same time, the epidemic affects economic activity depending on how well our households perceive the actual effects of economic activity on mortality. That is, the household's expected mortality generated from economic activity is subjective. The subjective expected effects of economic activity on mortality might differ from the actual effects and, in particular, households might underestimate these effects.

In this economy, our household chooses individual consumption c and hours worked h to solve:

$$\max_{\{c\geq 0, h\in[0,1]\}} u(c,h) + \delta\phi(h,\xi_{\mathcal{P}})\omega \tag{1}$$

subject to an individual budget constraint $c = wh$. A competitive firm produces consumption good using technology $y = zh$. Today's felicity is given by $u(c,h)$ which is increasing and concave

doing, how many people they come into contact with, etc. However, epidemiological frameworks do not—almost invariably—incorporate the endogenous behavior that leads to contagion. For the same token, previous economic models that assess the effects of an epidemic take the epidemic as given (e.g Young, 2005; Santaeulàlia-Llopis, 2008). However, endogenous contagion can be not only relevant to understand what factors determine the spread of a disease but also important to find optimal public policy against the spread. In this context, note that the nature of contagion—and hence the mechanisms needed to explain it—can differ by disease. For example, in the context of flu-like viruses—e.g. influenza, SARS and Covid-19—it is natural to focus on endogenous labor/leisure choices (e.g. Alvarez et al., 2020; Kaplan et al., 2020) whereas in the context of the HIV it is natural to focus on endogenous risky sexual behavior (see Greenwood et al., 2019; Aleman et al., 2020b). The growing literature on Covid-19 also includes Aspri et al. (2021), Bognanni et al. (2020), Casares et al. (2020), Eichenbaum et al. (2020), Farboodi et al. (2020), Fajgelbaum et al. (2020), Garibaldi et al. (2020), Glover et al. (2020), Jones et al. (2020), and Toxvaerd (2020) among many others. This growing literature also includes testing and quarantine policies; see Berger et al. (2020), Obiols-Homs (2020) and Piguillem and Shi (2020), among others.

[2] This work relates to previous stage-based studies. In particular, Iorio and Santaeulàlia-Llopis (2011) define stages of the HIV epidemic mapping country-specific epidemics to a single (average) epidemic path in order to explore the relationship between education and the probability of being infected with HIV over the course of the epidemic. More generally, the notion of epidemic stages is also analogous to the stylized stages of economic development (e.g. Lucas, 2004) and the demographic transition (e.g. Greenwood et al., 2005).

in consumption, c, and leisure, $1-h$. Tomorrow's felicity is given by a constant $\omega > 0$—which we can interpret as the value of being alive—discounted by factor δ times the household's perceived survival rate. Let the perceived survival rate be,

$$\phi(h, \xi_{\mathcal{P}}) = 1 - \zeta\lambda(h, \xi_{\mathcal{P}}),$$

where $\zeta > 0$ is the mortality rate after infection and $\lambda(h, \xi_{\mathcal{P}}) \in [0, 1]$ is the perceived probability of infection. The probability of infection and the associated mortality risk are perceived insofar our household does not know much h determines infections, the extent of which is truly captured by a parameter $\xi \in [0, 1]$. Although our household does not know the actual ξ, it has a subjective expectation (a belief) on it, $E^{\mathcal{P}}[\xi] = \xi_{\mathcal{P}}$, and acts according to it.

In particular, we are after infection processes satisfying $\lambda_h > 0$ and $\lambda_{h,\xi} > 0$ and we assume,

$$\lambda(h, \xi_{\mathcal{P}}) = \xi_{\mathcal{P}} h^{\alpha}, \tag{2}$$

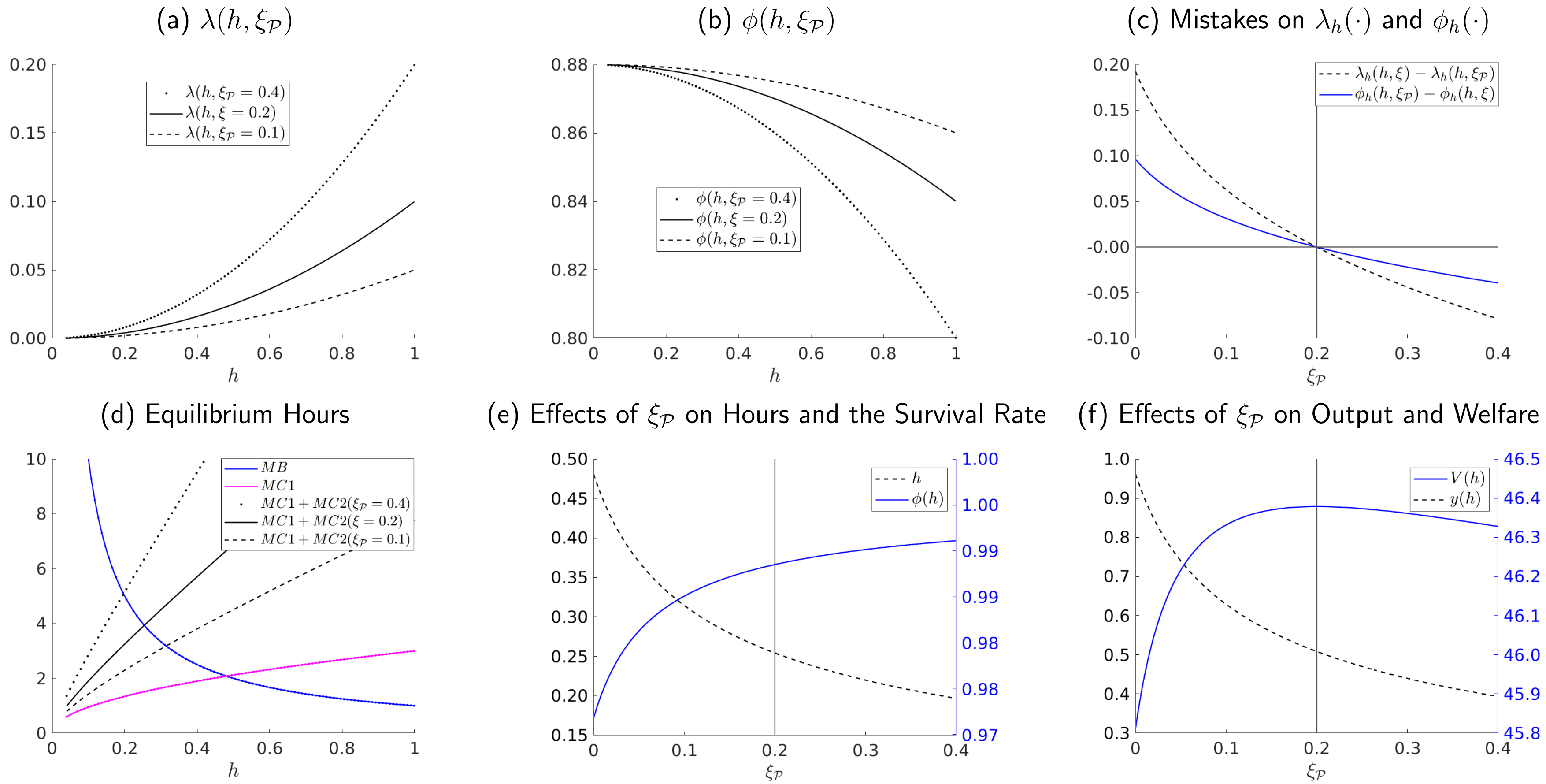
with $\xi_{\mathcal{P}} \in [0, 1]$ and $\alpha \geq 0$. Note that since $h \in [0, 1]$, the parameters $\xi_{\mathcal{P}}$ and α ensure that $\lambda(h, \xi_{\mathcal{P}})$ is a probability. Under this infection process, for a given α, the higher is h the higher are the odds of infection. Further, these effects of h on infections are larger the larger is $\xi_{\mathcal{P}}$; see panel (a) in Figure 1. In particular, if the belief $\xi_{\mathcal{P}}$ is smaller than the actual ξ, i.e. $\xi_{\mathcal{P}} < \xi$, then the household underestimates the actual effect of h on infections. Precisely, for any pair α and h, the household believes that infections generated by a level of activity h will be $\frac{\xi_{\mathcal{P}}}{\xi} < 1$ times lower than what they actually are. The opposite occurs if the household overestimates the odds of infection, i.e. $\xi_{\mathcal{P}} > \xi$. In this manner, if the actual ξ is equal to 0.2, a $\xi_{\mathcal{P}} = 0.1$ ($\xi_{\mathcal{P}} = 0.4$) implies that the household believes that economic activity generates half of (twice) the infections that it actually generate. Further, note that since $\lambda_h > 0$, then $\phi_h < 0$. That is, an increase in h decreases the survival probability; see panel (b) in Figure 1.

We can define the magnitude of the underestimation (or overestiation) of the actual infection process and survival rates. Agents believe that one extra unit of h will generate $\lambda_h(h, \xi_{\mathcal{P}}) = \xi_{\mathcal{P}}\alpha h^{\alpha-1}$ new infections. However in reality it generates $\lambda_h(h, \xi) = \xi\alpha h^{\alpha-1}$. The difference between these two is the error agents make:

$$\varepsilon_{\lambda(h,\xi_{\mathcal{P}})} = \lambda_h(h, \xi_{\mathcal{P}}) - \lambda_h(h, \xi) = (\xi_{\mathcal{P}} - \xi)\alpha h^{\alpha-1} \tag{3}$$

Both the errors in terms of the infection process, $\varepsilon_{\lambda(h,\xi_{\mathcal{P}})}$, and survival rates, $\varepsilon_{\phi(h,\xi_{\mathcal{P}})}$, are shown in panel (c) of Figure 1. If $\xi_{\mathcal{P}} < \xi$, then agents underestimate the infections and deaths. The opposite occurs with $\xi_{\mathcal{P}} > \xi$.

Figure 1: Economic Activity and Public Health Trade-Offs in a Pandemic



Notes: We assume $u(c, h) = \ln c - \kappa \frac{h^{1+\frac{1}{\nu}}}{1+\frac{1}{\nu}}$. The marginal benefit of working is $u_c w = \frac{1}{h}$, the marginal loss of leisure is $u_h = \kappa h^{\frac{1}{\nu}}$ and the marginal loss of lives is $\delta \phi_h \omega = \delta \zeta \alpha \xi h^{\alpha - 1} \omega$. Parameter values: $\delta = 0.9524, \xi = 0.2, \omega = 50, \kappa = 3, \nu = 2, \zeta = 0.5, z = 2, \alpha = 2$

The amount of economic activity in equilibrium is determined by the following first order condition of problem (1) with respect to h:[3]

$$\underbrace{u_c(c,h)w}_{\substack{\text{MB of Working:}\\ \text{Consumption Gain}}} = \underbrace{u_h(c,h)}_{\substack{\text{MC1 of Working:}\\ \text{Loss of Leisure}}} + \underbrace{\delta\phi_h(h,\xi_{\mathcal{P}})\omega}_{\substack{\text{MC2 of Working:}\\ \text{Loss of Lives}}} \tag{4}$$

together with market clearing.[4] Wages w are determined by the marginal product of labor. Equation (4) shows the trade-off between the marginal benefit (MB) of working which generates income (hence consumption) and the marginal cost of keeping economic activity up that consists of two terms: A first term that captures the loss of leisure associated with working (MC1) and a second term that captures the loss of discounted welfare from the deaths generated from infections due to economic activity (MC2).

In this manner, the economy pins down the equilibrium h by explicitly considering the trade-off between economic activity and public health, see panel (d) of Figure 1. For our illustration, we assume $u(c,h) = \ln c - \kappa\frac{h^{1+\frac{1}{\nu}}}{1+\frac{1}{\nu}}$. The strict concavity in consumption means that the MB decreases with h in a convex fashion (blue line). The MC of working associated with the loss of leisure increases with h (pink line).[5] Here, note that for a given h, the MB of working and the MC of working associated with the loss of leisure do not depend on the effects of h on infections. Therefore, absent an epidemic (i.e. with $\lambda_h(h,\xi) = 0$), the equilibrium h is determined by the crossing of MB and MC1. In this numerical example, we find that the amount of hours worked without epidemic $h^*(\xi = 0) = 0.48$. In contrast, in the presence of an epidemic (i.e. with $\xi > 0$) the marginal cost of working increases by the loss of lives generated from economic activity which shifts the MC line up. This implies that the equilibrium amount of hours worked in an epidemic are lower. In an epidemic, our household takes into account the loss of welfare associated with economic activity and is willing to reduce consumption in order to increase the probability of survival and reduce deaths in the economy. How large the drop in hours in response to the epidemic is depends on how well our household understands the process of infection. In particular, if our household is fully aware of the true process of infection (i.e., if $\xi_{\mathcal{P}} = \xi$) (black solid line) the reductions of hours relative to an economy without epidemic will be larger than if our household underestimates how many infections are caused by economy activity, that is, if $\xi_{\mathcal{P}} < \xi$ (black dashed line). Indeed, in our numerical example we find that $h^*(\xi_{\mathcal{P}} = \xi = 0.2) = 0.25$ and $h^*(\xi_{\mathcal{P}} = 0.1 < \xi) = 0.31$. In the extreme, if our household believes that economic activity generates no infection, i.e. $\xi_{\mathcal{P}} = 0$, then it will behave as if there was no epidemic. In contrast,

[3] Explicitly: $u_c = \frac{\partial u(c,h)}{\partial c}$, $u_h = \frac{\partial u(c,h)}{\partial h}$ and $\phi_h = \frac{\partial \phi(h,\xi_{\mathcal{P}})}{\partial h}$.

[4] That is, labor demanded by the firm equates labor supplied by the household. The goods markets also clears.

[5] With $\nu > 1$, this MC is strictly concave.

if our household overestimates the infections caused by economic activity, i.e. $\xi_{\mathcal{P}} > \xi$, then the reductions of hours will be larger than that from an economy where households are fully aware of the true process of infection. That is, our household shows an excess of caution. Indeed, in our numerical example we find that $h^*(\xi_{\mathcal{P}} = 0.4 > \xi) = 0.19$.

In panel (e) of Figure 1, we show the effects of $\xi_{\mathcal{P}}$ on the equilibrium amount of hours. The lower is $\xi_{\mathcal{P}}$, the larger are the equilibrium hours. The effect of $\xi_{\mathcal{P}}$ shows the opposite effect on the survival probability $\phi(h)$. That is, the lower is $\xi_{\mathcal{P}}$ the larger is the amount of infections and deaths. Clearly, there is a trade-off between economic activity and public health. Finally, we show how output and welfare varies with $\xi_{\mathcal{P}}$; see panel (f) in Figure 1. Output strictly measures economic activity generated from h and welfare takes into account not only output (hence consumption) but also the cost associated with the potential loss of life. Note that maximum welfare is achieved when the beliefs are correct, i.e. $\xi_{\mathcal{P}} = \xi$. Relative to when beliefs on ξ are correct, if our household underestimates the effect of economic activity on contagion, i.e. $\xi_{\mathcal{P}} < \xi$, then output is larger but, at the same time, the amount of deaths are also larger. The loss of welfare from the loss of lives dominates the increase in output implying that underestimation of the effects of economic activity yields lower welfare than that with correct beliefs. Instead, if our household overestimates the effect of economic activity on contagion, i.e. $\xi_{\mathcal{P}} > \xi$, then output is lower relative to when beliefs on ξ are correct and the amount of deaths are also lower. However, the welfare gains associated with reductions in the amount of deaths are dominated by the welfare losses from output reductions which implies a total loss of welfare relative to a household aware of the correct ξ. In other words, the equilibria to the right of the correct beliefs ($\xi_{\mathcal{P}} > \xi$) shows an excess of cautiousness, whereas to the left of the correct beliefs ($\xi_{\mathcal{P}} < \xi$) our households are incautious.

2.1 An Epidemic Path Endogenous to Economic Activity

Here, the previous model is extended to an infinite horizon as proposed in Aleman et al. (2020a).[6] Consider a one-household economy with many agents that is unexpectedly hit by an epidemic at time $t = 1$ with an initial number of infections of $I_1 > 0$. We normalize the pre-pandemic

[6]Note that the model purposefully ignores other potentially important channels in which an epidemic is determined by economic activity. I name a few. First, the occupation-industry mix is important to determine contagion risk (Houstecka et al., 2021). Second, the ability to telework can cushion the effect of the pandemic (Dingel and Neiman, 2020), in particular, when stay-home policies (or similar) are in place (Eyméoud et al., 2021). Third, the pandemic can alter consumption habits in manner that there are sector-specific persistent shocks (Barrero et al., 2020). Fourth, economic policy—e.g. increase in unemployment eligibility and benefits, implementation of short-time work, stimulus packages—can be coupled with public health policy (Cajner et al., 2020; Chetty et al., 2020) and in ways that can differ across countries or regions (Eyméoud et al., 2021). Fifth, agents could learn about the odds of infection during an epidemic (Aleman et al., 2020b).

population, N_0, to one. A representative household solves:

$$\max_{\{c_t \geq 0, h_t \in [0,1]\}_{t=0}^{\infty}} \sum_{t=0}^{\infty} \delta^t \Pi_{\tau=0}^{t} \phi(h_{\tau-1}, \xi_{\mathcal{P}}) u(c_t, h_t; \omega) \tag{5}$$

where the evolution of the population follows $N_t = \Pi_{\tau=0}^{t} \phi(h_{\tau-1}, \xi_{\mathcal{P}})$ and $\phi(h_{t-1}, \xi_{\mathcal{P}}) \in [0,1]$ is a survival probability that we define below.[7] Note that there is no fertility in this economy and, hence, the evolution of the population is solely determined by survival. Our household is subject to a per period budget constraint $N_t c_t = w_t h_t N_t$ and production occurs with technology $Y_t = z h_t N_t$. Wages are determined by the marginal product of labor, $w_t = z N_t$. Individuals can be either susceptible S_t, infected I_t, recovered R_t or dead D_t. Then, the total alive population is $N_t = S_t + I_t + R_t$. Agents perceive that the evolution of the population follows:

$$X_{S,t} = -\lambda(h_t, \xi_{\mathcal{P}}) \beta \frac{I_{t-1}}{N_{t-1}} S_{t-1} \tag{6}$$

$$X_{I,t} = \lambda(h_t, \xi_{\mathcal{P}}) \beta \frac{I_{t-1}}{N_{t-1}} S_{t-1} - \gamma I_{t-1} \tag{7}$$

$$X_{R,t} = (1-\zeta) \gamma I_{t-1} \tag{8}$$

$$X_{D,t} = \zeta \gamma I_{t-1} \tag{9}$$

where $X_{G,t} = G_t - G_{t-1}$ for $G = \{S, I, R, D\}$.[8] Conditional on randomly meeting an infected individual at rate $\frac{I_{t-1}}{N_{t-1}}$, a susceptible individual beliefs to get infected with probability $\lambda(h_t, \xi_{\mathcal{P}})\beta$. The parameter β can capture features like density, age-health structure of the population, pollution or occupation-industry composition (among others) that could potentially differ across locations. The believed probability of infection depends on economic activity h with $\lambda(h, \xi_{\mathcal{P}}) = \xi_{\mathcal{P}} h^{\alpha}$. The true dynamics however are given by $\lambda(h, \xi) = \xi h^{\alpha}$. In this manner, the parameter $\xi_{\mathcal{P}} \in [0,1]$ captures how much our household believes that economic activity h affects new infections. Hence, if $\xi_{\mathcal{P}} < (>) \xi$, then households believe that their actions generate less (more) infections and deaths that what they actually do. If death occurs, it does so after working and consuming. That is, the perceived survival rate between t and $t+1$ equals to:

$$\phi(h_t, \xi_{\mathcal{P}}) = 1 - \frac{X_{D,t}}{N_{t-1}} \tag{10}$$

and the probability of surviving to period t is $\Pi_{\tau=0}^{t} \phi(h_{\tau-1}, \xi_{\mathcal{P}})$.

[7] More generally, $N_t = N_0 \Pi_{\tau=0}^{t} \phi(h_{\tau-1}, \xi_{\mathcal{P}})$. We have normalized N_0 to one.

[8] Note that we assume that recovered individuals are neither infectious nor can become infected.

The amount of economic activity h_t is determined by the following Euler condition:

$$\underbrace{u_{c_t}(c_t, h_t)w}_{\substack{\text{MB of Working:}\\ \text{Consumption Gain}}} - \underbrace{u_{h_t}(c_t, h_t)}_{\substack{\text{MC of Working:}\\ \text{Loss of Leisure}}} = \underbrace{\delta\phi_{h_t}(h_t, \xi_{\mathcal{P}})u(c_{t+1}, h_{t+1})}_{\substack{\text{MC of Working:}\\ \text{Loss of Lives}}} \qquad \forall t. \tag{11}$$

which is a second order difference equation in h_t that can be easily solved with multiple software apps. We need an initial and terminal conditions which we find by solving the pre-pandemic $t < 0$ equilibrium before the unexpected arrival of the pandemic at $t = 0$. In this pre-pandemic era there are no infections and $\phi(h_t) = 1$, which implies that the equilibrium h_t for $t < 0$ is computed by setting the right hand side of (11) to zero in which case h_t simply solves an intratemporal trade-off. The same occurs after the pandemic disappears.

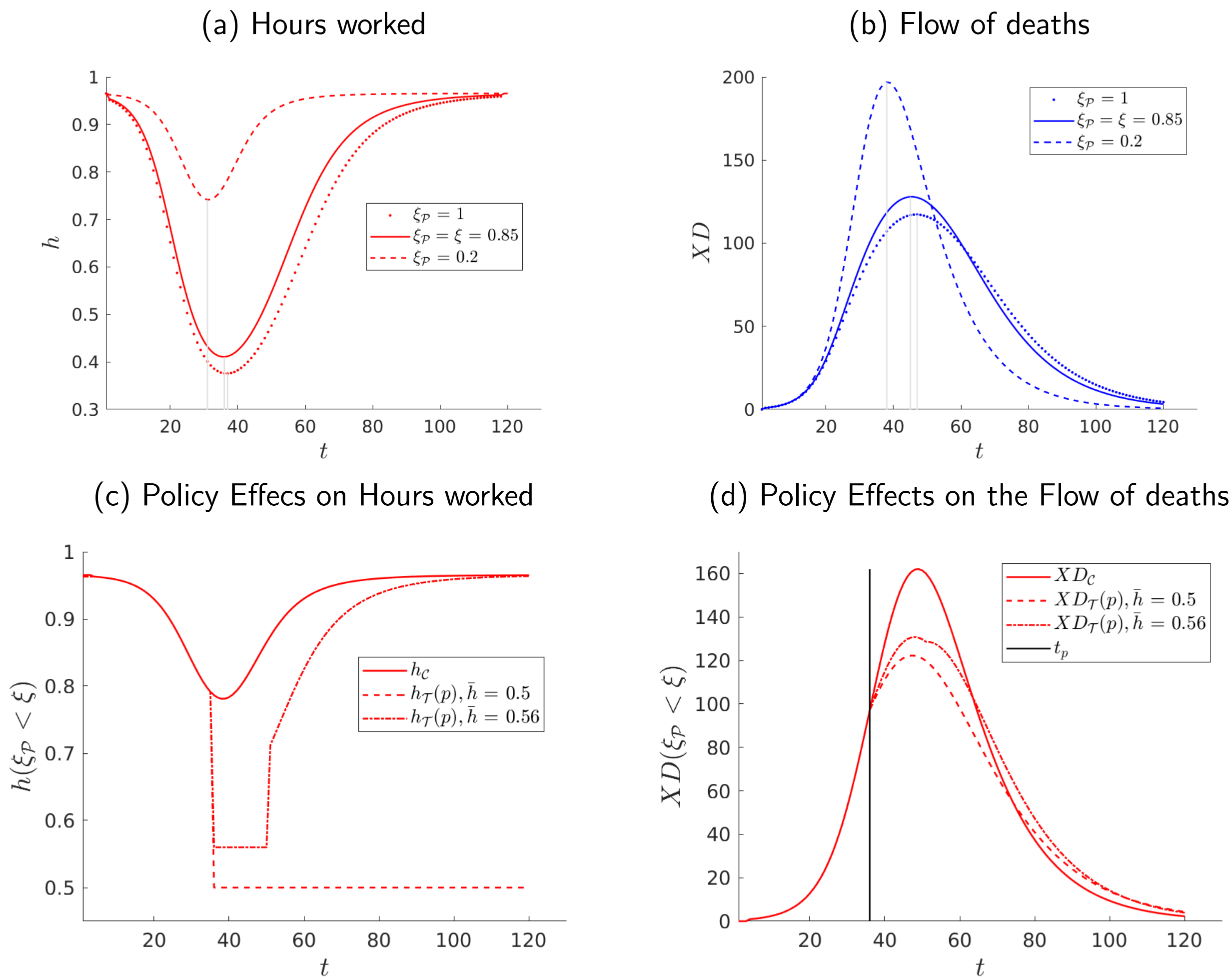
Even though agents perceive the flow deaths and survival rate in (10), each period they are unexpectedly hit by the actual survival rate $\phi(h_t, \xi)$. This implies that each period, after the shock is realized, households need to readjust their labor choice. We do not allow the agents to learn about the correct ξ, so even though they are hit by the actual population deaths they are unaware that their prediction error is due to the mistakes in the perceived infection rate. In panel (a) of Figure 2, we show the evolution of economic activity h_t for three $\xi_{\mathcal{P}}$ where we assume that the correct ξ equals 0.85. In panel (b) of Figure 2, we show the endogenous evolution of the epidemic in terms of the flow of deaths, $X_{D,t}$ over the course of the epidemic.[9] [10]

When households are aware of the correct infections process, i.e., $\xi_{\mathcal{P}} = \xi = 0.85$, we find that the equilibrium hours decrease to a minimum of 0.41 reached in period $t = 36$. In terms of the flow of deaths, this implies a peak of 127 in $t = 45$. The accumulated number of deaths in this case where agents are aware of the correct ξ is 6,153. If households underestimate the effects of economic activity on infections (and deaths), i.e. if $\xi_{\mathcal{P}} = 0.2 < \xi = 0.85$ then the reduction of hours is less pronounced reaching a minimum of 0.74 in period $t = 31$. This lower reduction in hours comes at the cost of a larger amount of deaths with a peak of 196 reached in period $t = 38$. The accumulated number of deaths in this case where agents undertestimate the effects

[9] To solve this model we use the following steps: (step 1) Given initial values SIR_t and h_t, compute true $SIR_{t+1}(\xi)$ using equations (6) to (9) with $\lambda(h_t, \xi)$. If $t = 0$, $h_{t=0}$ is given by the pre-pandemic hours and $N_0 = 6M, I_0 = 1000, R_0 = 0, D_0 = 0$ and $S_0 = N_0 - I_0 - R_0 - D_0$; (step 2) Given h_t guess a sequence of hours worked $\{\hat{h}_\tau\}_0^{T-t}$ and simulate the believed evolution of the epidemic $\{SIR\tau\}_{t+1}^T$ using the believed sequence of infection probabilities $\{\lambda(h_t, \xi_{\mathcal{P}})\}_t^T$; (step 3) Iterate on the sequence of $\{h_\tau\}_0^{T-t}$ until the Euler equation (11) is solved at every period; and (step 4) from the previous solution set $h_{t+1} = h_{\tau=0}$ update $t = t + 1$ and go back to step 1, stop if $t = T$.

[10] Note that although we are focusing on a single wave of the epidemic, it is relatively easy to introduce new waves of the epidemic by allowing for exogenous jumps in the amount of infected, by changing β's or other parameters that reflect different (e.g more contagious) strands of the virus, or by allowing for policy to stop too early.

Figure 2: Endogenous Epidemic Path and Policy Effects



Notes: We choose, $\xi = 0.85, \xi_{\mathcal{P}} = 0.2, \nu = 2.6, \kappa = 1.05, \omega = 560400, \theta = 1, z = 64, \delta = 0.952, \beta = 0.383, \gamma = 1/12, \zeta = 0.0011, N_0 = 6M, I_0 = 1000, lag = 2,$ .We use $u(c_t, h_t) = \ln c_t - \kappa \frac{h^{1+\frac{1}{\nu}}}{1+\frac{1}{\nu}} + \omega$.

of economic activity on deaths is, 6,418. In contrast, if households overestimate the effects of economic activity on infections (and deaths), i.e. if $\xi_{\mathcal{P}} = 1.0 > \xi = 0.85$ then the reduction of hours is more pronounced reaching a minimum of 0.37 in period $t = 37$. This larger reduction in economic activity shapes the amount of deaths that now reach a peak of 117 reached in period $t = 47$. The accumulated number of deaths in this case where agents overtestimate the effects of economic activity on deaths is, 6,077.

2.2 The Effects of Public Health Policy on Economic Activity and the Epidemic

There are different public health policies that can be used against a pandemic. We focus on the stay-home policies widely implemented across the globe against the Covid-19 pandemic.[11] In the context of our model, this implies imposing a constraint $h < \overline{h}$ for a given interval of time in which the policy is in place from period (day) t_p to t_f.

We now discuss the results of imposing a constraint of $\overline{h} = 0.5$ for a (long) interval of time from period $t_p = 36$ to $t_f = 250$ (dashed line). There are effects of such policy on hours because the policy is binding in the sense that without the stay-home policy the equilibrium path of hours (solid line) shows higher economic activity than what the policy dictates for the entire interval of time in which the policy is in place; see panel (c) of Figure 2. In particular, at the period the policy is implemented the equilibrium h_{t_p} is 0.8, whereas the policy sets h to a lower value of 0.5. The lower economic activity has consequences for the flow of deaths that now peaks by a lower magnitude (and earlier) relative to a model economy without policy; see panel (d) of Figure 2. Finally, implementing an alternative stay-home policy of $\overline{h} = 0.56$ for a (short) interval of time from period $t_p = 36$ to $t_f = 51$ (dotted line) also implies a policy effect though by a lesser magnitude on both hours and the flow of deaths.

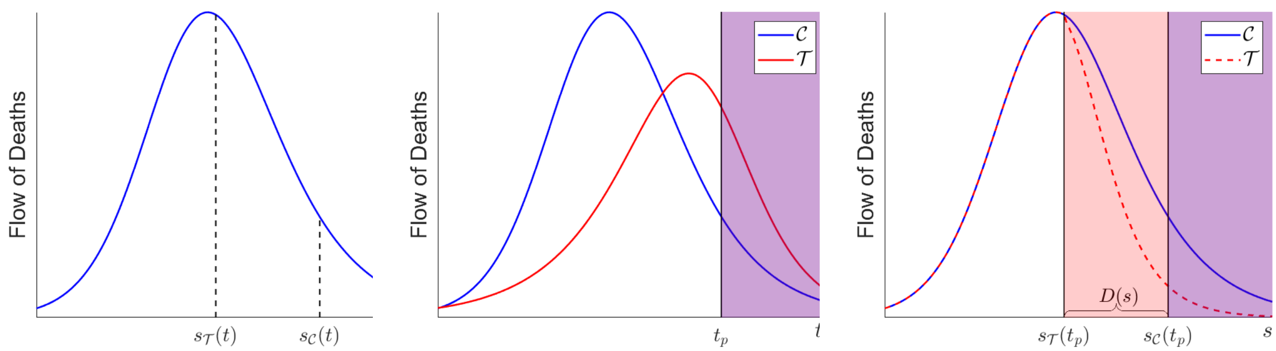
3 A Stage-Based Identification of Policy Effects with an Application to Covid-19 (Aleman et al., 2020a)

The empirical evaluation of policy effects typically relies on cross-regional (or group) variation in the time of policy implementation. In that context, an ideal scenario is one in which two regions that would be otherwise identical in terms of an outcome variable of interest differ in that a "treated" region ($\mathcal{T}$) implements a policy at time t_p and a "control" region ($\mathcal{C}$) does not. In that setting, where absent of policy these two regions are identical, the difference in the outcome variable that emerges across regions after t_p is the effect of policy. In this context, Aleman et al. (2020a) propose a new methodology where the standardly used variation in the time of policy implementation is not necessary to evaluate the effectiveness of policy. In this Section, I describe this methodology that exploits cross-regional stage variation of the outcome variable of interest at the time of policy implementation in order to identify policy effects—even in instances where the policy is implemented at the same time across all regions. Aleman et al. (2020a) apply this

[11] Alternatively, in the context of the economy that we postulated, a government that knows ξ could nudge the economy's households to learn about the actual effects of economic activity. This would imply that after the nudging households privately decide to change their prevention behavior providing less labor in equilibrium. Note that this exercise would require the government to know both the true ξ and the $\xi_{\mathcal{P}}$ believed by households which poses a problem that we think deserves further discussion.

Figure 3: The Evolution of an Epidemic: An Illustration with Two Regions, Extracted from Aleman et al. (2020a)

(a) A Stylized Epidemic Path (b) Before Normalization (c) After Normalization



methodology to economic growth policies, demographic policies and public health policies.

3.1 Identification of policy effects: Constructing the counterfactual epidemic

The novel key insight of the proposed approach in Aleman et al. (2020a) is that stage variation of the outcome variable of interest can exist across regions even at the same calendar time. For example, in the context of an epidemic with the outcome variable of interest being the flow of deaths, there exists cross-regional variation in the stage of the epidemic: namely, at a given point in time there is heterogeneity in how far regions moved along an epidemic path in terms of the flow of deaths. This is illustrated in panel (a) of Figure 3, which shows a stylized epidemic path in terms of the daily flow of deaths associated with an epidemic. Imagine that two regions go through the same path. If the epidemic in region $\mathcal{C}$ starts earlier than in region $\mathcal{T}$, then at the same calendar time t the epidemic is in a more advanced stage in region $\mathcal{C}$.

In reality, there is not only heterogeneity in the calendar date at which an epidemic starts. Precisely, epidemics can differ across regions in several dimensions—such as the speed of disease diffusion and the magnitude (or overall death toll). Panel (b) of Figure 3 illustrates the time-path of the epidemic of two example regions, where policy is effective at time t_p in both, but the epidemic in region $\mathcal{C}$ starts earlier, evolves faster and has a larger magnitude than in region $\mathcal{T}$.

The proposed method consists of normalizing the time, speed and magnitude of the epidemic paths across regions. In particular, the normalization ensures that all regions share the same normalized epidemic path before the effective policy date t_p. This is illustrated in panel (c) of Figure 3. In this manner, the normalization unveils an interval $D(s)$——the orange shaded area in panel (c)——within which the epidemic path in region $\mathcal{T}$ is affected by the policy but the epidemic path of region $\mathcal{C}$ is not. Accordingly, on this interval, the path of $\mathcal{C}$ describes the counterfactual path for $\mathcal{T}$—i.e., the flow of deaths region $\mathcal{T}$ would have experienced had the policy reform not been implemented. Hence, the difference between the paths across the two regions can be used to estimate the policy effect.

3.2 A Montecarlo Analysis of the Identification Strategy

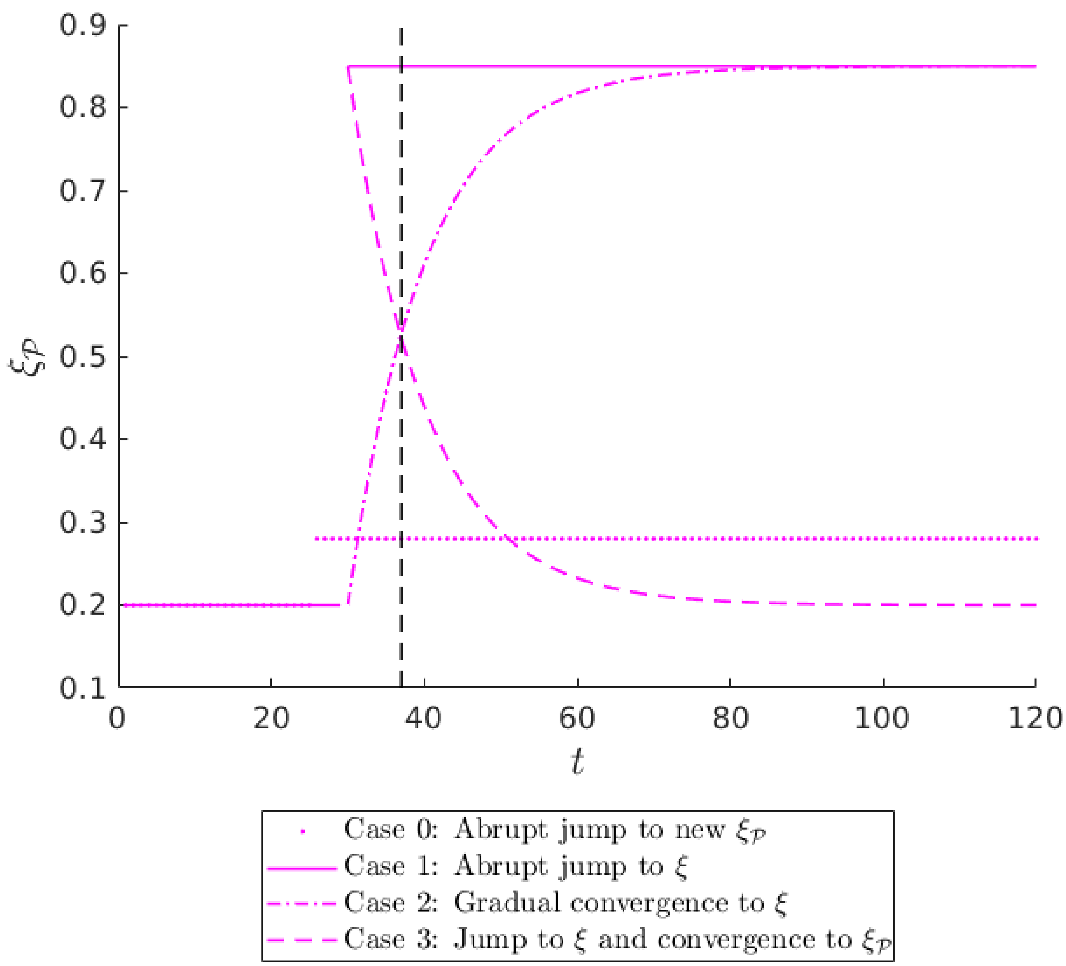
To assess the newly proposed strategy to identify policy effects, Aleman et al. (2020a) conduct a montecarlo analysis. The idea is to apply the new empirical identification to model-generated data and assess whether the empirical strategy correctly recover the actual model effects of policy. We focus on a Montecarlo analysis with two modeled regions that follow different epidemic paths but are subject to the same nationwide stay-home policy. In particular, we create two regional epidemic paths that are endogenous to economic activity following the model posed in Section 2.1. The epidemic paths across these two regions are heterogeneous in that we assume that a region ($\mathcal{C}$) is characterized by a larger β and an earlier starting date of the epidemic; see panel (a1) of Figure 6. The stay-home policy of $h = 0.5$ is implemented from $t_p = 38$ to $t_f = 250$ in both regions. The implications of such policy for hours worked is in panel (a2) of Figure 6. Clearly, the policy is binding, which implies that the policy has an effect on deaths. The difference between the flow of deaths without policy (solid line) and the flow of deaths with policy (dashed line) are the true policy effects, as generated from the model; see panel (a1) of Figure 6.

Panel (a3) of Figure 6 shows the results from using the stage-based identification taking the model simulated data with policy as the only observable data to the econometrician interested in empirically assessing the effects of policy. In particular, the observed epidemics are the control region $\mathcal{C}$ (solid blue) and the treatment region $\mathcal{T}$ (dashed red). Note that in both cases the policy is implemented at $t_p = 38$ (until $t_p = 250$) depicted as the vertical (dashed gray) line. The mapping from $\mathcal{C}$ to $\mathcal{T}$ implemented in Aleman et al. (2020a) normalizes the pre-policy epidemic path of the control region to that of the treatment region (dashed blue with crosses).[12] The normalization implies an overlap interval of one week between $t_p = 38$ and $t = 44$ in which the treatment region is subject to the policy whereas the normalized control regions is not. Comparing the actual model-based percentage of lives saved in that overlap interval and the one estimated from the stage-based empirical identification we find, respectively, 9.53% and 10.33%. That is, the stage-based identification provides a good estimate of the actual effects of policy. In panel (b) of Figure 6 we re-conduct the same exercise but imposing in the model a pre-policy behavioral change in the control region $\mathcal{C}$ induced by an increase in $\xi_{\mathcal{P}}$ that moves closer to the actual ξ. This implies a pre-policy reduction in the equilibrium hours. From the perspective of

[12] Aleman et al. (2020a) show that mapping $\mathcal{C}$ to $\mathcal{T}$ delivers identical results to mapping $\mathcal{T}$ to $\mathcal{C}$.

an empirical strategy aimed to assess policy effects, the change in the model $\xi_{\mathcal{P}}$ generates time-varying unobserved heterogeneity in the control region. Note that we purposefully left the actual effects of policy on region $\mathcal{T}$ unchanged. We find that our stage-based identification is robust to this type of heterogeneity; see panel (b3) in Figure 6. In the overlap interval, the estimated percentage of lives saved is 10.92 which, again, is close to the true effects, 9.53.

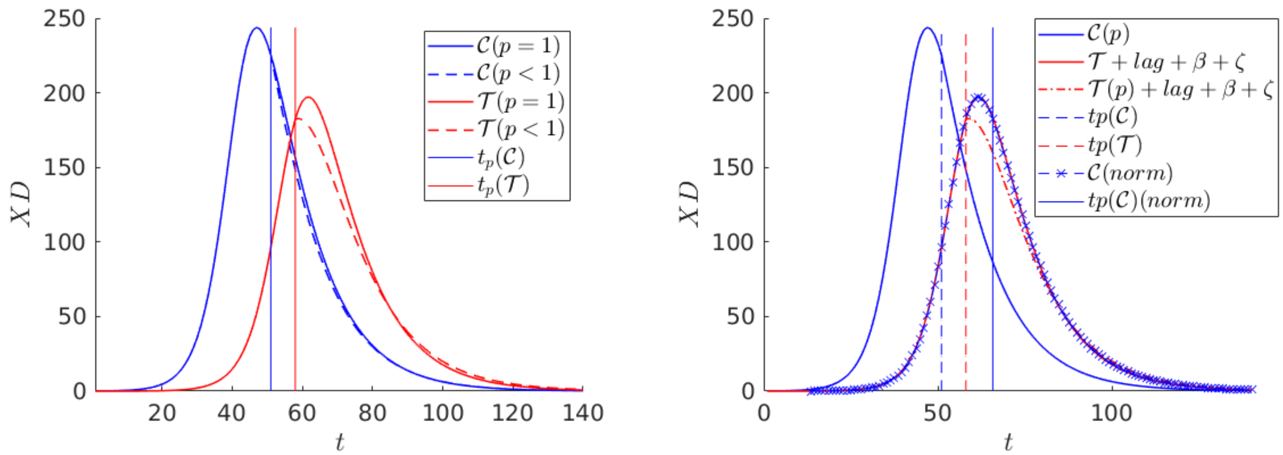
Figure 4: Change in $\xi_{\mathcal{P}}$



Notes: Change in $\xi_{\mathcal{P}}$

Figure 5: Case of Reversal

(a) Before Normalization (b) After Normalization

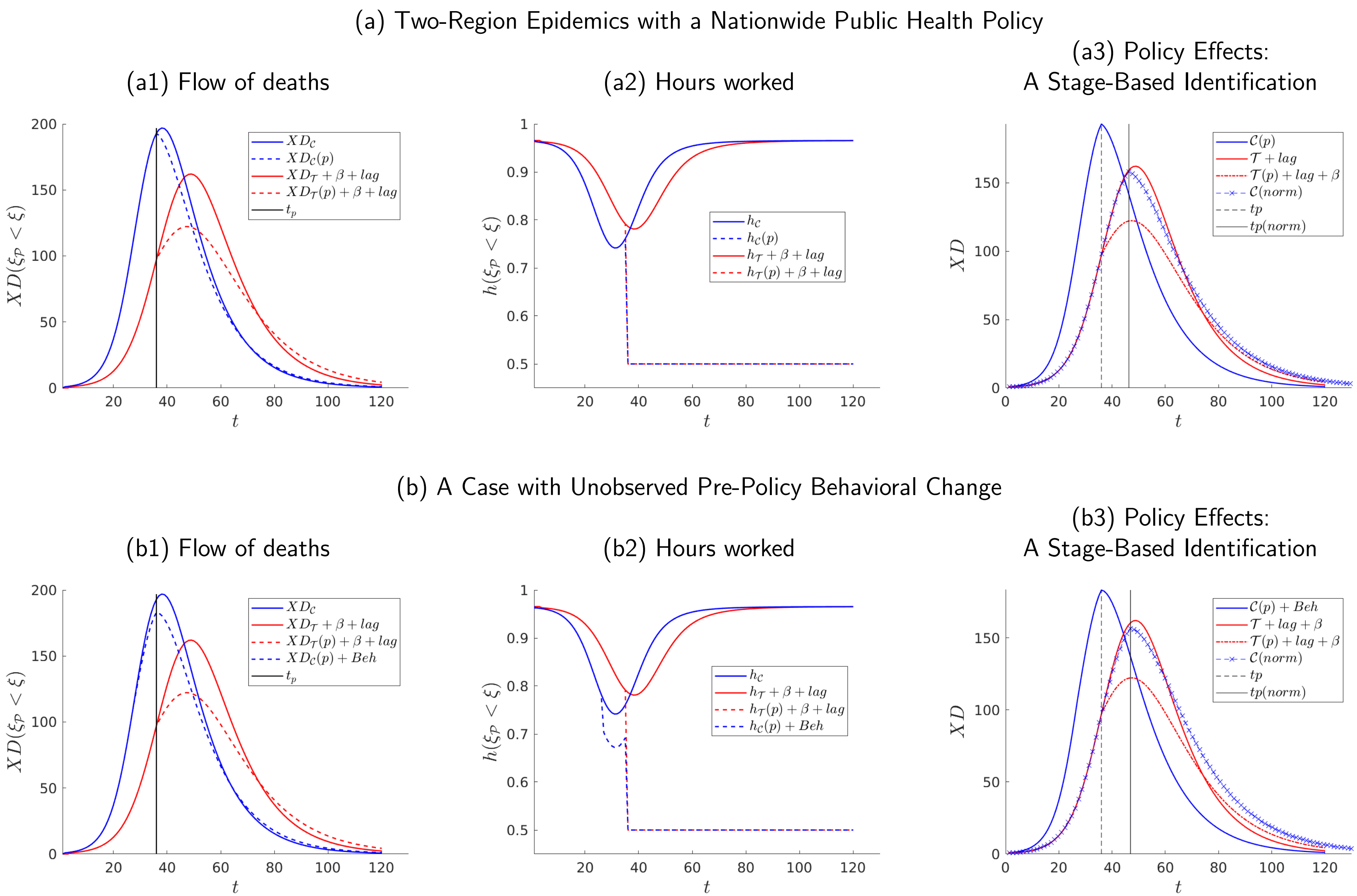


Notes: With $tp(\mathcal{C}) = 51$, $tp(\mathcal{T}) = 58$ and $tp(\mathcal{C})(norm) = 65.7$.

3.3 The Stay-Home Policy Effects Against Covid-19 in Spain

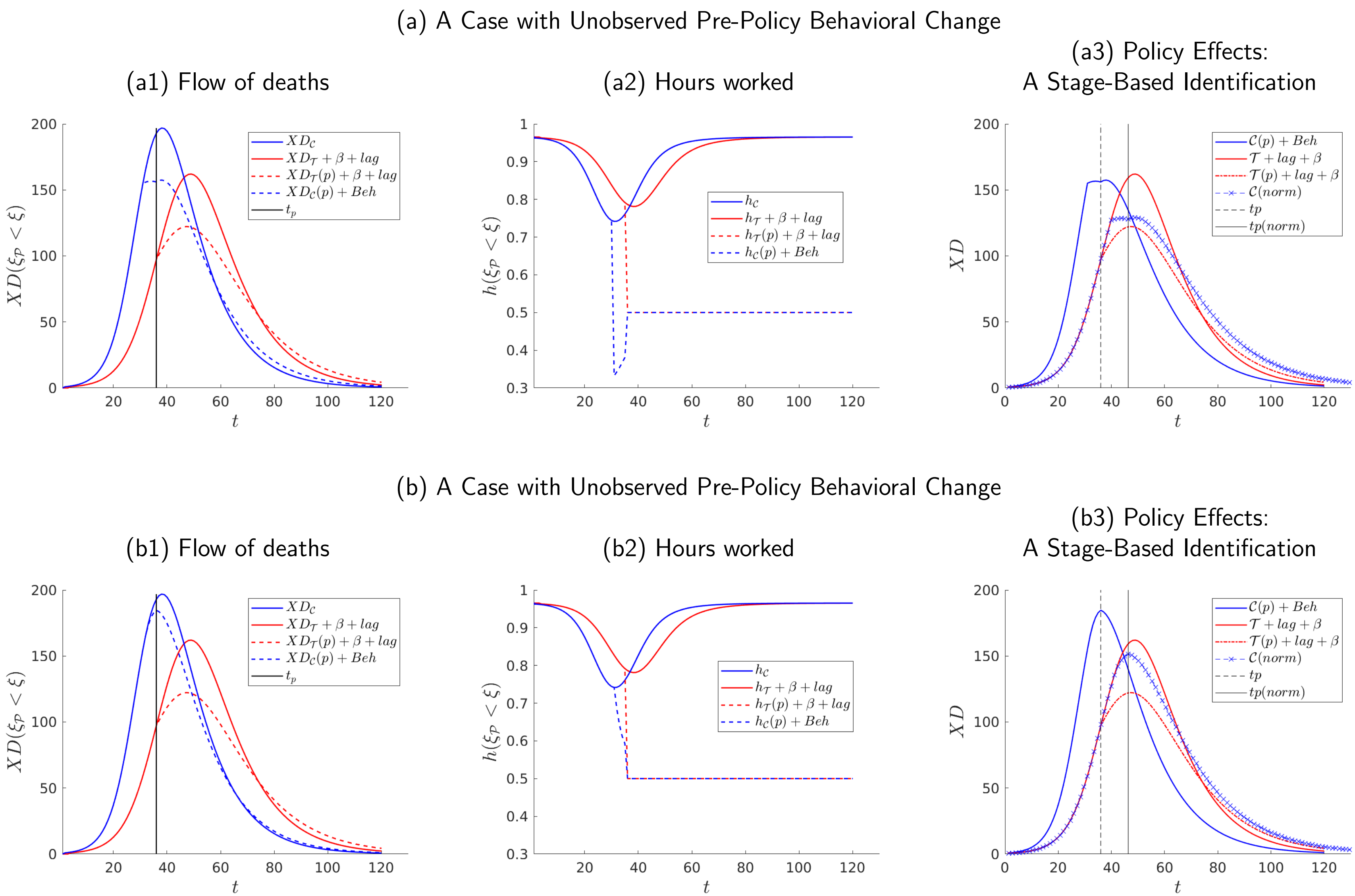
The stay-home policy—or 'lockdown'—in Spain was implemented nationwide from March 14 to May 2, when the strictest measures were lifted. Note that considering that it takes on average 12 days from infection to death, the effects of policy should surface starting in March 27. As benchmark, Aleman et al. (2020a) use Madrid as the control region $\mathcal{C}$ that provides the counterfactual for the Rest of Spain (RoS) that conforms the treatment region $\mathcal{T}$. The use of Madrid as leading region is corroborated by the normalization procedure implemented in the paper. The normalization uncovers an overlap interval $D(s)$ of seven days during which the epidemic dynamics in RoS is subject to the policy, while the dynamics in Madrid are not (yet). Thus, using pre-policy data to normalize $\mathcal{T}$ to $\mathcal{C}$ implies that the distance in the ovarlap interval between the normalized RoS and Madrid measures the effect of policy. The estimated the percentage of lives saved on this overlap interval is 18.7%, which translates into 1,074 lives in RoS. Extrapolating this estimate of the percentage effect of the reduction of deaths from the seven days overlap interval until the end of the observation period on May 14 results in an estimate of 3,786 lives saved in the rest of Spain.

Figure 6: A Stage-Based Identification of Policy Effects: A Montecarlo Analysis with Model-Generated Data, Extracted from (Aleman et al., 2020a)



Notes: Where $\bar{h} = 0.5, t_p = 36, t_f = 250,$ *and behaviour change of* $\xi_{\mathcal{P}} = 0.28$ *occurs at* $t = 26$

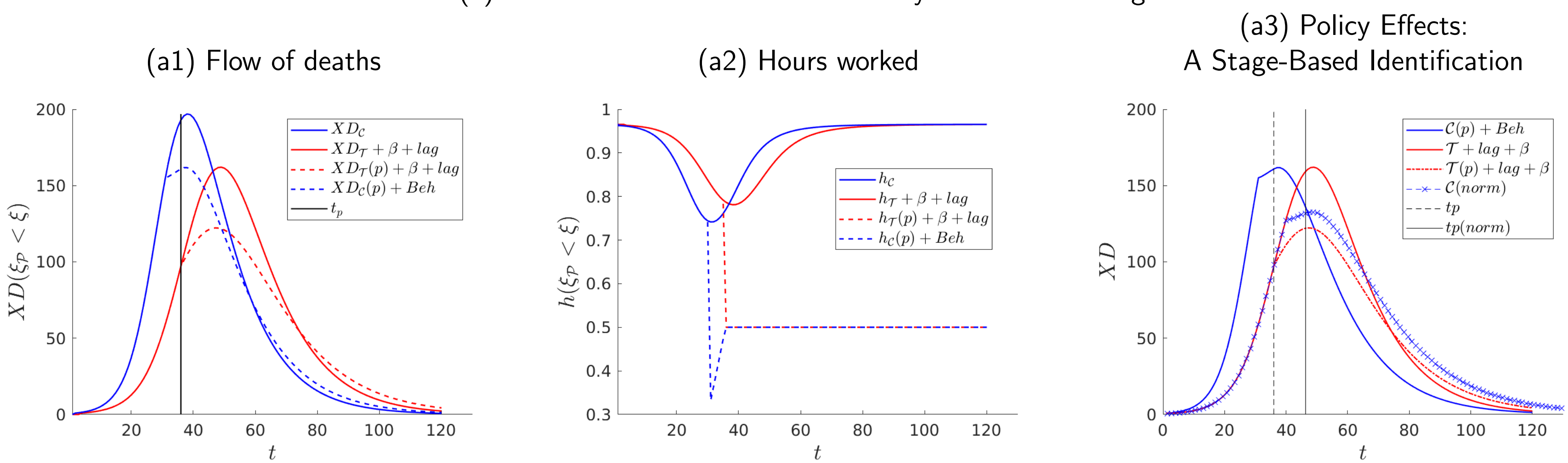
Figure 7: A Stage-Based Identification of Policy Effects: A Montecarlo Analysis with Model-Generated Data, Extracted from (Aleman et al., 2020a)



Notes: Where $\bar{h} = 0.5, t_p = 36, t_f = 250,$ *and behaviour change occurs at* $t = 30$

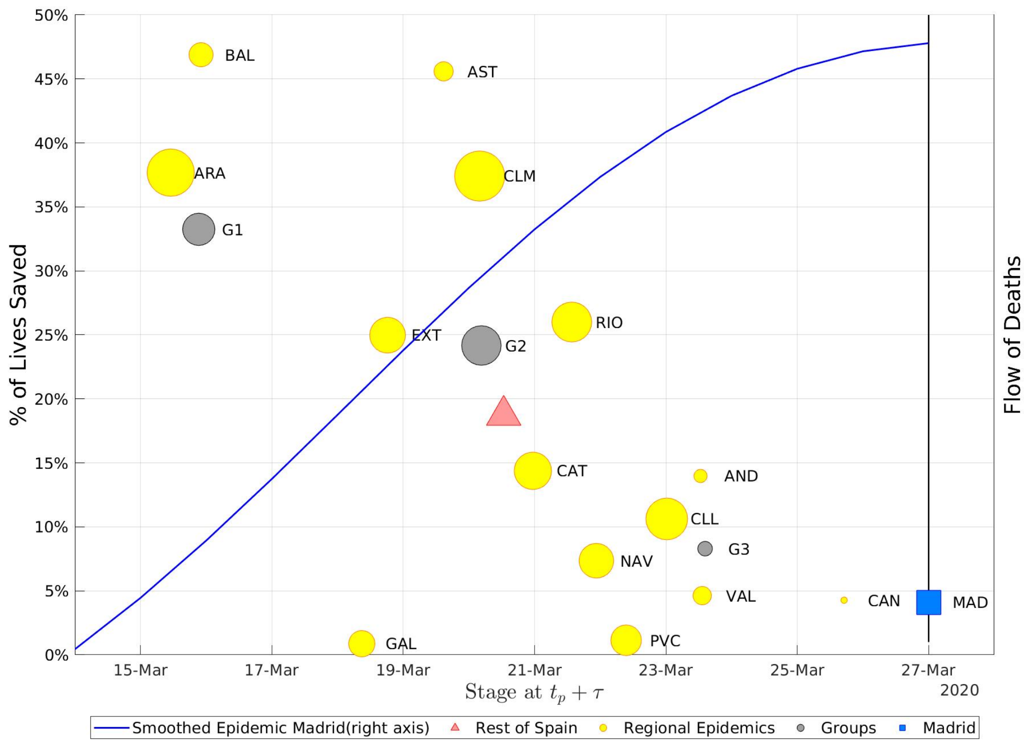
Figure 8: A Stage-Based Identification of Policy Effects: A Montecarlo Analysis with Model-Generated Data, Extracted from (Aleman et al., 2020a)

(a) A Case with Unobserved Pre-Policy Behavioral Change



Notes: Where $\bar{h} = 0.5, t_p = 36, t_f = 250$*, and behaviour change occurs at* $t = 30$

Figure 9: Effects of Stay-Home Policy: By Region, Extracted from (Aleman et al., 2020a)



Notes: Andalucia (AND), Aragon (ARA), Asturias (AST), Baleares (BAL), Canarias (CAN), Cantabria (CNT), Castilla-La Mancha (CLM), Castilla y Leon (CLL), Catalunya (CAT), Ceuta (CEU), Valencia (VAL), Extremadura (EXT), Galicia (GAL), Madrid (MAD), Melilla (MEL), Murcia (MUR), Navarra (NAV), Pais Vasco (PVC), La Rioja (RIO). Three subgroups (grey circles): Early-stage implementers (G1); Mid-stage implementers (G2); and Late-stage implementers (G3). The size of the yellow and grey circles is the stock of deaths per thousand inhabitants accumulated during the overlap period.

Further, regions in which the stay-home policy is implemented in earlier stages of the epidemic benefit the most in terms of the percentage of lives saved. This is summarized in Figure 9, which shows the region-specific effects of the policy by stage in the respective region. The size of the region-specific circles reflects the population size in the respective region. For instance, at the (effective) time of policy implementation (i.e., March 27) the normalized epidemic of Catalunya maps on the stage of the epidemic that Madrid had in March 21. This advantage of 6 days tripled the percentage of lives saved by the policy in Catalunya 14.5% relative to Madrid, 4.7%. As a further illustration of the importance of the stage of policy implementation Figure 2 also shows three aggregate regions: early-stage (G1), mid-stage (G2) and late-stage (G3) policy implementers. The authors estimate that at early stages (G1) the policy is four times more effective than at lager stages (G3).

4 Conclusion

This note exemplifies the close link between economic activity and the evolution of an epidemic with a simple labor supply model where infections are generated by economic activity such as Covid-19, SARS or the common flu. In this illustrative model the endogenous tradeoff between economic activity and the evolution of a pandemic is explicit and therefore taken into account when evaluating public health policy. It is perhaps fair to say that this interrelationship between economic activity and a pandemic (and in which many economists have worked, see the introduction) has probably been paid little attention to by public institutions when designing optimal policy against the Covid-19 pandemic.

For example, we now know that the confinement of Spain against the first wave of the Covid-19 arrived late. If the same policy had been applied a week earlier, the same policy would have quadrupled percentage of lives saved. This evidence if policy effects can be used to better discipline the so-called "econ-epi" models that should help us better choose our public policy against future pandemics.

One channel that seems important to incorporate, given the effect of belief on what the infection process is in our model, is the possible learning that during the pandemic make as many citizens as the government on the specific characteristics of its own epidemic such as, for example, what is the mode of infection and what are the probabilities of infection in different scenarios along the lines of what Aleman et al. (2020b) do in the context of HIV. Equally, the process of learning about the effectiveness of some policies, such as the use of the mask, could be important.

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