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Managing resilience and viability of supranational supply chains under epidemic control scenarios

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1 Managing resilience and viability of supranational  
2 supply chains under epidemic control scenarios.

3 — Author's Version —

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8 **Abstract**

A comprehensive model is presented to evaluate the *resilience* and *viability* of supranational supply chains under various epidemic control scenarios. The model integrates a multiplex network of socially connected individuals subjected to a probabilistic SEIRSD epidemic, as well as production configurations monitored for performance capacity. The epidemic evolution within this system depends on four primary cost factors: deployed control strategy, health policy implementation, the value of human life, and economic productivity loss due to the epidemic. These costs are adjusted for GDP differences between countries in the network and are influenced by factors such as the duration and severity of confinement, vaccination efficacy, and healthcare capacity. A Nash equilibrium analysis of SEIRSD load-based costs is employed to identify optimal control strategies. Time To Recovery (TTR) and Longitudinal Service Level (LSL) are used as metrics for assessing the resilience and viability of supply chains. The convergences and conflicts of control strategies are evaluated using TTR and LSL, providing insights into the impact of public health measures on supply chain performance. This methodology offers a framework for policymakers and supply chain managers to make informed decisions during prolonged epidemic conditions. Numerical simulations illustrate the conditions for convergence and conflict between epidemic control policies and supply chain objectives, highlighting the need for dynamic policy adjustments to ensure supply chain resilience and viability.

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## 9 1. Introduction

10 When a global calamity strikes, various governmental mitigation strate-  
11 gies are implemented worldwide, adding further profound impact on in-  
12 dustry and business processes. The most recent case in point, the COVID-19  
13 pandemic, prompted diverse policies from governments and health author-  
14 ities globally, resulting in significant local and global economic downturn  
15 ([Jackson et al., 2021](#); [Ajmal et al., 2021](#); [Lofvers, 2020](#)). The manufactur-  
16 ing, processing, and shipping sectors along supply chains experienced  
17 unpredictable disruptions to their performance capacities, inventory issues,  
18 stockouts, and price surges in first materials and commodities ([Lofvers,](#)  
19 [2020](#); [Hille, 2021](#); [Ardolino et al., 2022](#)). Public policymakers have deployed  
20 several control strategies based on epidemic dynamics modeling to mitigate  
21 the impacts ([Bertozzi et al., 2020](#); [Godio et al., 2020](#); [Reicher and Stott, 2020](#);  
22 [Boucekkine et al., 2021](#); [MacIntyre et al., 2021](#); [Xu et al., 2021](#); [Yang, 2021](#);  
23 [Amir and Boucekkine, 2022](#); [Dobson et al., 2023](#)).

24 These control strategies, which involve different forms of social distanc-  
25 ing to limit transmission and vaccination policies to boost immunity, aim to  
26 minimize the epidemic burden—quantifiable in both economic and human-  
27 life terms—within their respective territory. However, these measures inter-  
28 rupt normal industrial and business operations. The performance of supply  
29 chains and epidemics converge in their core property of diverse geographic  
30 industrial and business implantation, and interdependence of labor actors.  
31 This interdependence is crucial in a social population where it is also the  
32 enabling factor of disease propagation. In supply chain networks the diver-  
33 sified localization of service and production and their interdependence is  
34 a contingent business structure derived from planning, cost optimization,  
35 and product complexity requiring the assembling and dispatching of first  
36 and derived materials. The interconnection in these networks entails that  
37 a disruption in one location can quickly affect operation in others, similar  
38 to how a virus spreads through a population. The common underlying  
39 feature of interdependence between the same population of individuals  
40 allows –possibly up to a scale factor– their functioning as common nodes in  
41 two layers on one network. The simultaneous implementation of different  
42 mitigating strategies by international policymakers has a complex impact on  
43 supranational supply networks. Our previous work ([Broekaert et al., 2024b](#))  
44 aimed to predict how international supply chains could be reconfigured  
45 following policymakers’ mitigation strategies. First, a game-theoretic ap-

46 proach was employed in our model to derive Nash equilibrium profiles from  
47 diverging control strategies by connected countries with different GDPs,  
48 based on optimal Epidemic Control Costs (ECC).<sup>1</sup> Then, from a matrix  
49 of throughput Loss and Migration Costs (LMC) for divergent policies, a  
50 method was derived to assess potential supply chain reconfigurations.

51 In our current study, we analyze how diverse control policies converge  
52 or conflict with supply chain-centered objectives. Our method starts by  
53 deriving the Epidemic Control Cost (ECC) matrix for divergent mitigation  
54 policies of two international policymakers and determining the optimal  
55 Nash strategy profile. In contrast, alternative optimal Nash strategy profiles  
56 are determined for two core supply chain metrics. Comparing these supply  
57 chain metric-based Nash profiles with the ECC-based Nash profiles reveals  
58 conditions for convergence and conflict of mitigation strategies. Our original  
59 contribution presents managers and policymakers with a framework to  
60 comprehend how public policies affect and should be informed by supply  
61 chain performance.

62 In an interconnected contact network spanning different countries, and  
63 where epidemic control policies mutually influence outcomes, the *resilience*  
64 and *viability* of international supply chains are consequently affected ([Ivanov](#)  
65 [and Dolgui, 2020](#)). To formally assess these supply chain characteristics,  
66 we propose appropriate metrics: the resilience of supply chains, monitored  
67 through their Time To Recovery (TTR), and the viability of supply chains,  
68 quantified using their Longitudinal Service Level (LSL).<sup>2</sup> The Time To Re-  
69 covery measures the time a supply chain –or a defined portion of it– takes  
70 to recover its normal operational performance after a disruption, with a  
71 shorter TTR indicating higher resilience. The Longitudinal Service Level,  
72 based on the practical Service Level –the percentage of customer demand  
73 met without delay from the available inventory– monitors the robustness  
74 in meeting a series of process-impacting shocks while keeping an effective  
75 service. The Longitudinal SL impacts customer satisfaction and market  
76 competitiveness by demonstrating reliability in meeting customer demand  
77 over time. Emphasizing the longitudinal aspect using LSL then assesses  
78 the long-term viability of supply chains under repeated disruptions.

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<sup>1</sup>The ECC in our model is formally defined in Eq. (12).

<sup>2</sup>Both metrics TTR and LSL are formally defined in Eqs. (2) and (7) respectively. See also e.g. [Ruel et al. \(2024\)](#) and [Falasca and Zobel \(2008\)](#) for alternative uses.

79 Our study details the convergences and conflicts in control policies for a  
80 configuration involving two regions, capturing the basic dynamics of large-  
81 scale contact networks. Under disruptions, supply chain managers seek a  
82 control strategy profile that *minimizes* the TTR and *maximizes* the LSL of their  
83 supply chains. Policymakers, referred to as 'players' in a strategic game,  
84 determine the optimal control policy for each epidemic wave by considering  
85 the Nash equilibrium of the ECC. The cost-based Nash equilibrium dictates  
86 the isolation measures and control profiles for policymakers, focusing on  
87 public cost optimization, which may conflict with supply chain managers'  
88 concerns.

89 This Nash strategic profile impacts both TTR and LSL and its monitor-  
90 ing hence allowing the assessment of supply chain *resilience* and *viability*.  
91 Besides the Nash equilibrium of the ECC, the policymakers can identify  
92 the Nash equilibria for TTR and LSL to inform their policy, or alternatively,  
93 they can directly identify an optimal strategy for a weighted scalarized goal  
94 encompassing all three. Hence, continuous monitoring of TTR and LSL  
95 can enable dynamic policy adjustments in response to changing epidemic  
96 conditions, ensuring that supply chains remain resilient and viable over  
97 time.

98 The remainder of the paper is organized as follows. Section 2 reviews  
99 significant literature on supply chain behavior under disruptions, particu-  
100 larly epidemiological models on social-contact networks. Section 3 covers  
101 the concepts of the multiplex model with a production layer to model sup-  
102 ply chain activity levels, providing TTR and LSL metrics informing supply  
103 chain managers, and an epidemiological layer informing the ECC for policy-  
104 makers. Here the specific epidemic model is detailed, obtaining its acronym  
105 from the defining population segments or characteristics related to the  
106 stages of the disease; *Susceptible*, *Exposed*, *Infectious*, *Recovered* and *Dead*,  
107 resulting in the 'SEIRSD' model - now with a second 'S', due to including  
108 the process of waning immunity.<sup>3</sup> Section 4 explains the methods and for-  
109 mal dynamics that underlie the encompassing supply chain & epidemic  
110 system, while the exact mathematical formalism is relayed in [Appendix A](#)  
111 and [Appendix B](#). Section 5 presents numerical outcomes for health con-  
112 trol strategies from Nash equilibria of ECC, TTR, and LSL, on a simulated  
113 network epidemic, along with an analysis of conditions for conflicts and

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<sup>3</sup>The shorthand SEIRD is used to denote the *separate* characteristics.

114 convergences in optimal control policies. Here based on our model metrics,  
115 the framework for policymakers and supply chain managers emerges to  
116 make informed decisions during prolonged epidemic conditions, ensuring  
117 the resilience and viability of supply chains. Finally, Section 6 concludes by  
118 emphasizing our key insights into evaluating the resilience and viability of  
119 supply chains under control policies, as well as outlining the next steps for  
120 future research.

## 121 2. Literature overview

122 This section briefly reviews the literature on epidemic networks and their  
123 impact on supply chain resilience and viability, as well as game-theoretic  
124 approaches to managing these interdependencies.

125 **Supply Chain Resilience and Viability.** The concepts of resilience  
126 and viability in supply chains have been extensively studied. [Juan et al.](#)  
127 [\(2022\)](#) model the relationships among five components of supply chain re-  
128 siliance—visibility, velocity, flexibility, robustness, and collaboration—and  
129 their impact on performance during disruptions, identifying collaboration  
130 as a key driver. [Chowdhury and Quaddus \(2017\)](#) develop a resilience  
131 framework based on dynamic capability theory, highlighting proactive and  
132 reactive capabilities and supply chain design quality. [Ivanov \(2024b\)](#) used  
133 a hybrid bibliometric and expert approach to observe a shift from prepared-  
134 ness to recovery and proactive adaptation. Their related study ([Ivanov,](#)  
135 [2024a](#)), on the resilience of supply chains, implements an ontology akin  
136 to the immune system with characteristics of preparedness and recovery,  
137 respectively translated by innate and adaptive immunities in a living system.  
138 Resilience as a system-wide quality over multiple industries is explored  
139 by [Gruchmann et al. \(2024\)](#), their online surveysshow the main factors  
140 of proactive preparedness via anticipation and reactive responsiveness via  
141 agility. In [Echefaj et al. \(2024b\)](#), the relationships between adaptation ca-  
142 pabilities and practices ensuring operational continuity in supply chains  
143 were empirically tested and positively supported using responses from 252  
144 organizations.

145 The work of [Rozhkov et al. \(2022\)](#), focuses on the adaptivity of oper-  
146 ational decisions on preparedness and recovery in various network on-  
147 tologies, pre and peri-pandemic: in particular the impact of anticipatory  
148 inventory pre-positioning and en route adaptation of production-ordering  
149 policy. The COVID-19 pandemic has generated significant research on sup-

150 ply chain disruptions. Decision-support models using epidemic dynamics  
151 have been proposed (Paul et al., 2021; Ouardighi et al., 2022), and the ripple  
152 effect in supply chains has been modeled extensively (Borgatti and Halgin,  
153 2011; Mishra et al., 2019; Kinra et al., 2020; Li and Zobel, 2020; Park et al.,  
154 2021; Llaguno et al., 2021; Ivanov et al., 2020; Ivanov, 2020; Yu and Aviso,  
155 2020; Choi, 2021; Sawik, 2022; Scarpin et al., 2022; Brusset et al., 2022, 2023),  
156 e.g. with the effect of long-term disruptions qualitatively analyzed using  
157 secondary data from automotive and electronics industries by Kravchenko  
158 et al. (2024).

159 The authors Ruel et al. (2024) propose a resource-based scale for sup-  
160 ply chain viability using five factors ‘structure and mechanisms’, ‘system  
161 development’, and supply chain ‘redesign’, ‘feedback’, and ‘process’, and  
162 show its relation to supply chain performance under severe disruptions  
163 by providing a respondent-based nomological validation. Ivanov (2024c)  
164 explore adaptation- vs stability-based resilience, showing return to normal  
165 states compared to proactive adaptation are complementing quantitative  
166 and qualitative oriented protective approaches.

167 **Network Models** describe the dynamic interaction of diverse agents,  
168 ranging from individuals to firms, cities, or countries, in the movement of  
169 goods, wealth, people, labor, or health (Keeling and Eames, 2005; Newman,  
170 2018). For example, intertwined supply chain networks were studied by  
171 Echefaj et al. (2024a) for their effects on sourcing and recovery strategies and,  
172 showing its recovery processes deviate from conventional patterns. Recent  
173 studies have focused on individual-based ontologies and the architecture of  
174 contact graphs to implement mitigating factors and assess impacts on labor  
175 productivity (Das et al., 2023). Multiplex network approaches incorporate  
176 additional features, such as an information layer for disease awareness  
177 diffusion (Fan et al., 2022) and competing opinions over social-contact net-  
178 works (Peng et al., 2021). These models enable a detailed assessment of the  
179 impact on supply chains. An optimized network-of-networks mechanism  
180 for cross-industry adaptation during crises was proposed for, and gains  
181 examined from, collaborative crisis preparedness by Dolgui et al. (2024).

182 **Control Policies and Epidemic Costs.** Epidemic models have been  
183 developed to assess the mitigating effects of control policies. Eryarsoy  
184 et al. (2023) solve a compartmental SEIRD-model with time-dependent  
185 infection rates and government stringency indices. Chen et al. (2023) build  
186 a SIRD-model linking social distancing policies to financial market stability.

187 The overall epidemic cost has been modeled by several studies (Charp-

188 [entier et al., 2020](#); [Reddy et al., 2021](#); [Gros et al., 2021](#); [Gollier, 2021](#); [Plazas](#)  
189 [et al., 2021](#)). Long-term effects on wealth redistribution are considered by  
190 [Boucekkine and Laffargue \(2010\)](#), while [Huberts and Thijssen \(2023\)](#) de-  
191 velop a non-pharmaceutical mitigation model to minimize social epidemic  
192 costs.

193 **Game-Theoretic Approaches.** The interconnection of populations on a  
194 global contact network means local control policies impact epidemic out-  
195 comes beyond their jurisdictions. The COVID-19 pandemic highlighted the  
196 need for regulatory flexibility and political enabling for effective supply  
197 chain management ([Farahani et al., 2023](#)). [da Fonseca et al. \(2023\)](#) demon-  
198 strate the importance of firm-to-firm technology transfer for large-scale  
199 vaccine production. Game-theoretic models have been used to study com-  
200 petitive acquisition of medical supplies ([Salarpour and Nagurney, 2021](#))  
201 and the optimal allocation of resources ([Nagurney et al., 2016](#); [Nagurney,](#)  
202 [2021a,b](#)). These models highlight the co-determinacy of epidemic outcomes  
203 due to interlinked populations and the necessity for collaborative strategies.

### 204 3. The supply chain and epidemic network model

205 Building on previous studies involving our epidemic model ([Broekaert](#)  
206 [et al., 2022, 2024c,a,b](#)), we adopt a multiplex graph ontology that integrates  
207 a supply chain production layer with the population’s social contact layer  
208 under a SEIRSD epidemic dynamic. The model incorporates distinct epi-  
209 demic *control strategies* deployed by two interconnected population groups  
210 on the contact graph –which can typically be referred to as ‘regions’ or  
211 ‘countries’. These controls induce changes in the graph topology and pop-  
212 ulation characteristics over time, resulting in a temporally heterogeneous  
213 epidemic graph model, e.g. Fig. 1. The new features in our current model  
214 facilitate the description of supply chain *viability* and *resilience*.

215 Basically, an individual-based network model spans a *graph* by linking all  
216 human individuals -or nodes - that experience a ‘person-person’ interaction  
217 that can cause the contagious disease to spread. These shared-location-  
218 based networks have a different topology in comparison to ‘social networks’  
219 based on social media connections ([Barrett et al., 2009](#); [Prasse et al., 2021](#)).

220 Our models utilize an individual-based ontology and a probabilistic  
221 approach to provide the necessary variables for a quantitative analysis of  
222 *resilience* and *viability*. Each individual’s probabilities of carrying disease  
223 characteristics in the supply chain form the basis for the expressions of Time

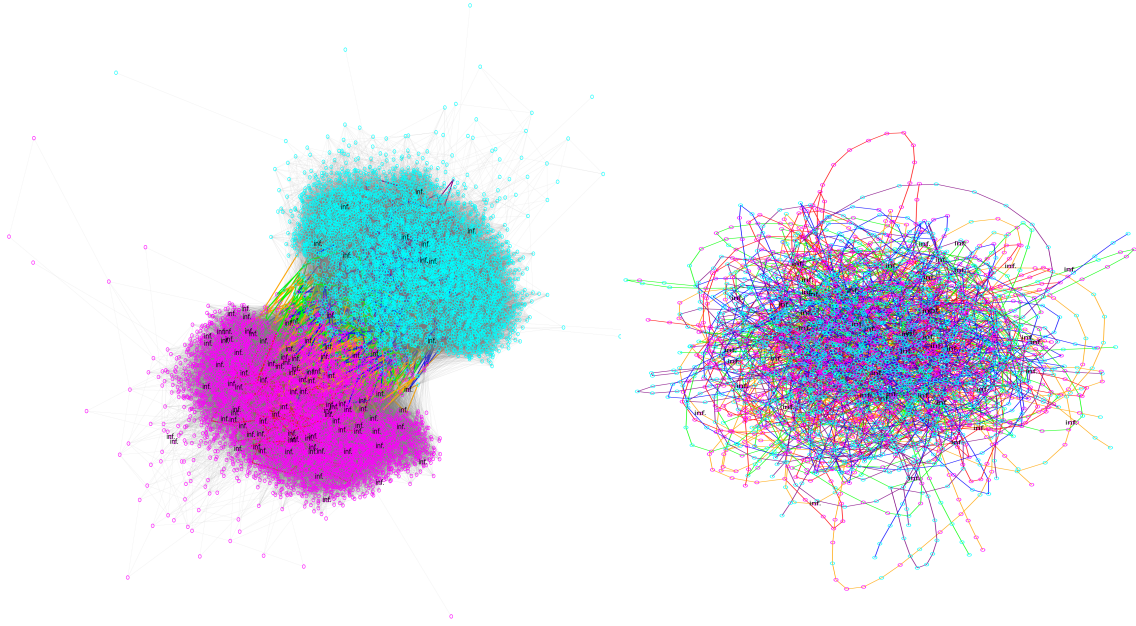


Figure 1: A simulated multiplex network (left) with supply chains spanning two distinct but interconnected regions (magenta vs. cyan) within a designed social contact graph  $\mathcal{G}(V_g, E_g)$  with  $N = 10^4$  nodes, constructed using an optimized adjacency algorithm. For clarity, the  $I_{fs01}$  isolation is depicted, which causes the full separation of the two regions. In each simulation of a controlled epidemic, ten random supply chains are tested for each of the varying spreads between the regions. The supply chain layer (right) groups the node sets that are active within and between the regions. The color coding for the spread values over the two regions is as follows:  $\{0 : \text{'purple'}, .25 : \text{'blue'}, .5 : \text{'lime'}, .75 : \text{'orange'}, 1 : \text{'red'}\}$ . Note that a spread value of 0 represents a supply chain entirely within group\_1, while a spread value of 1 represents a supply chain entirely within group\_0. Intermediate spread values indicate a mix of inter-group supply chains. The initially infected nodes are labeled 'inf.' and, mainly occur in group\_0. ( $init\_infected\_wave1=100, spread\_infect=.9$ )

224 To Recovery (TTR) and Longitudinal Service Level (LSL). The TTR and  
 225 LSL metrics serve as proxy expressions for the concepts of *resilience* and  
 226 *viability* in supply chains, respectively. Various other metrics were proposed  
 227 to cover the inherent adaptability of the supply chain, particularly due to  
 228 internal factors associated with mass customization manufacturers. Among  
 229 these, the Time-to-Adapt (TTA) metric was introduced, which measures  
 230 the time period from the onset of disruptions until actions are taken by the  
 231 manufacturer to mitigate the effects (Mosayebi et al., 2024).

232 In the SEIRD epidemic model, each individual is assigned probabilities  
 233 for possessing attrited characteristics (Exposed, Infectious, and Dead ) and  
 234 healthy characteristics (Susceptible and Recovered). These epidemic charac-

235 teristics change for each individual over time and depend on their contacts  
 236 and epidemic control measures, as illustrated in Fig. 2. Their values influ-  
 237 ence an individual’s health and, consequently, the effective performance  
 238 capacity of the supply chains in which they operate, as expressed by the  
 239 SEIRD-based definitions of TTR and LSL.

240 **Time To Recovery - Using SEIRD Probabilities for TTR.** In the SEIRSD  
 241 model, the recovery process is captured by the transition from the Infected  
 242 (I) state to the Recovered (R) state. However, also the Susceptible (S) state  
 243 qualifies an individual to participate in the Supply Chain (SC) activities.  
 244 For each node  $k$  in the supply chain subset  $V_{SC}$ , the total probability of  
 245 being in a performing state at time  $t$  is  $p_{R_k}(t) + p_{S_k}(t)$ . This metric is hence  
 246 the core parameter to assess the well-being of each individual  $k$  and their  
 247 capability to perform labor. In the worst of the disease, this metric could  
 248 drop low to 0 while someone uninfected or vaccinated will remain close to  
 249 1. It is hence crucial to know this metric for all people performing labor in a  
 250 given supply chain. The expected Time To Recovery for individual  $k$  can  
 251 be derived from the projected recovery probability over time, according to  
 252 Eq. (B.1) which governs the epidemic spreading in a network. It suffices  
 253 to extract the moment in time when this individual has regained sufficient  
 254 capacity to regain labor activity. The TTR for the entire supply chain (SC),  
 255 with node subset  $V_{SC}$ , can be defined as the average time at which its  
 256 nodes have transitioned to a sufficiently performant state ( $S$  and  $R$ ). After  
 257 having evolved past the maximum peak value of the Exposed and Infected  
 258 components in time, lowered probabilities in these components may not be  
 259 indicative of disease incapacitation anymore. Accordingly, to encompass  
 260 the variable degrees of *operational* recovery, a *performance threshold* value on  
 261 the activity level  $p_{R_k} + p_{S_k}$  is set above which an individual is considered to  
 262 be capable of effectively performing labor again.<sup>4</sup>

263 Formally, for each node  $k$  in  $V_{SC}$ , the expected recovery time  $TTR_k$  can  
 264 be estimated as the time when  $p_{R_k}(t) + p_{S_k}(t)$  again reaches a threshold  
 265 value `perf_thresh`, after having passed its minimum activity level:

$$TTR_k = \min\{t \mid p_{R_k}(t) + p_{S_k}(t) \geq \text{perf\_thresh and } t > t_{\min_k}\} \quad (1)$$

---

<sup>4</sup>The probabilistic node-states under the governing equations Eqs. (B.1) cannot, from a mathematical point of view, fully recover because the D-characteristic operates as a *sink* in the dynamics.

266 In real-world epidemics, practical considerations should decide the thresh-  
 267 old value `perf_thresh`. The specific nature of the supply chain may require  
 268 more stringent (e.g. medical, nursing, or elderly care) or permissive (agri-  
 269 cultural, nautical, or industrial) thresholds. In the present simulation model  
 270 with COVID-19 parametrization, the threshold is set to a demographic aver-  
 271 age, `perf_thresh = .7`, inciting labor re-activation under prolonged adverse  
 272 conditions. The aggregated  $TTR_{V_{SC}}$  for the supply chain subset  $V_{SC}$  can be  
 273 taken as the *average* of the node-level  $TTR_k$ , with  $k \in V_{SC}$ . Ultimately, the  
 274 robust metric for assessing the supply chain's TTR is derived by averaging  
 275 the  $TTR_{V_{SC}}$  for a large sample,  $N_{SC}$ , of supply chains – with the same typical  
 276 regional spread – to obtain:

$$TTR = \frac{1}{N_{SC}} \sum_{i=1}^{N_{SC}} \sum_{k \in V_{SC_i}} \frac{TTR_k}{|V_{SC_i}|} \quad (2)$$

277 which is essentially dependent on the epidemic wave ( $w$ ), the spreading of  
 278 the supply chain over the regions (*spread value*), and the **Control Strategy**  
 279 profile CS –listed in Eq.(10). The current definition for TTR, Eq. (2), is  
 280 based on the underlying SEIRD model which expresses recovery and labor  
 281 capacity from epidemic metrics. In real-world configurations, these epi-  
 282 demic metrics will instigate higher-level disruptions that are not reversible  
 283 or suffer from substantial latency and which will prolong the effective TTR.

284  
 285 **Service Level - Using SEIRD Probabilities for SL.** The viability of a  
 286 supply chain is evaluated by determining its Service Level (SL) within a  
 287 longitudinal or multi-wave epidemic framework. In the proposed model,  
 288 the service level of a supply chain is correlated with the potential for activity  
 289 within the supply chain. Individuals performing in the supply chain, and  
 290 with a high probability of infection will reduce its overall service level.

291 The activity probability  $p_{A_k}$  of a node is defined as the sum of the sus-  
 292 ceptibility probability and the recovered probability:

$$p_{A_k}(t) = p_{S_k}(t) + p_{R_k}(t), \quad (3)$$

293 as these are the characteristics that allow disease-unburdened labor. In  
 294 the COVID-19-based SEIRSD model, only minor traces of Infected (I) and  
 295 Exposed (E) states, along with a relatively small death probability (D),  
 296 persist in the long term. Therefore, a minimum activity level during an

297 epidemic wave can be identified for each individual:

$$p_{A_k, \min} = \min\{p_{A_k}(t) | t \in [0, T_w]\} \quad (4)$$

298 i.e., for each individual in the supply chain, the minimum activity over time  
 299  $p_{A_k, \min}$  is considered an indicator of potential activity failure in the given  
 300 time window of the epidemic wave  $w$ . To capture the interdependence of  
 301 activity within the supply chain with subset  $V_{SC}$ , the activity metric of the  
 302 entire supply chain is calculated as the *harmonic* mean of the individual  
 303 minimum activity levels of its nodes:

$$A_{V_{SC}} = l_{SC} \left( \sum_{k \in V_{SC}} (p_{A_k, \min})^{-1} \right)^{-1}. \quad (5)$$

304 The harmonic mean is utilized because it emphasizes smaller values, en-  
 305 suring that nodes with lower activity levels have a more significant impact  
 306 on the overall metric. The robustness of the metric is practically assured by  
 307 averaging the activity levels  $A_{V_{SC}}$  of a number  $N_{SC}$  of supply chains with  
 308 the same characteristic *spread value*:

$$\bar{A}_{V_{SC}} = \frac{1}{N_{SC}} \sum_{k=1}^{N_{SC}} A_{V_{SC}}. \quad (6)$$

309 This procedure avoids biased reporting of values based on the possibility of  
 310 *atypical* random sampling of nodes –see Section 4. To track the effect of the  
 311 control strategies (CS) on the supranational supply chains, the parameter  
 312 *spread value* indicates how many segments of the supply chain depend on  
 313 the health controls rolled out by each of the country’s policymakers. To  
 314 standardize its meaning the size of the supply chain node-set was fixed  
 315  $V_{SC_i} = l_{SC}$  for all  $i$ , and the spread value is defined to express the fraction  
 316 of the supply chain in country 0.

317 The longitudinal perspective of viability considers the repeated interrup-  
 318 tions of three consecutive epidemic waves, each characterized by a distinct  
 319 infectivity parameter ( $\beta$ ) and, for which the *initial* SEIRD state is reset by  
 320 combining new randomly infected individuals and the SEIRD-state of the  
 321 population inherited from the previous wave, Eq. (13). To obtain a longi-  
 322 tudinal metric, the average activity levels  $\bar{A}_{V_{SC}}$  of the supply chains in the

323 three consecutive epidemic waves are aggregated according to the harmonic  
 324 mean:

$$\text{LSL} = n_{\text{waves}} \left( \sum_{w \in \{\text{waves}\}} (\bar{A}_{V_{SC}|w,CS})^{-1} \right)^{-1} \quad (7)$$

325 A higher value of LSL indicates a better resistance of the supply chain to  
 326 failure during epidemic outbreaks.<sup>5</sup> The LSL, as defined, is a longitudinal  
 327 metric that only depends on the spreading of the supply chain (*spread value*),  
 328 and the control strategy profile (CS).

329  
 330 **Epidemic contact layer.** The Person-person social-contact networks  
 331 are obtained by contracting the daily trajectories of the individuals over  
 332 shared spatial locations (like ‘home’, ‘sports venue’, ‘work’,...). Our models  
 333 use a (fast) algorithm to produce artificial networks that closely mimic  
 334 ‘person-person’ contact networks  $\mathcal{G}(V_g, E_g)$  (see detailed explanations in  
 335 (Broekaert et al., 2024c, 2022) and Appendix A).

336 The probabilistic SEIRSD-model describes each individual with *prob-*  
 337 *abilities* for the *characteristics* of being ‘Susceptible’, ‘Exposed’, ‘Infectious’,  
 338 ‘Recovered’ and ‘Dead’. Each node hence is provided with a state vector  
 339 with the five defining probabilities

$$\mathbf{\Pi}_k(t) = (p_{S,k}(t), p_{E,k}(t), p_{I,k}(t), p_{R,k}(t), p_{D,k}(t)), \quad (8)$$

340 where the index  $k$  runs over all individuals of the population of size  $N$ . By  
 341 regrouping the component for each characteristic, the formalism can be  
 342 expressed on  $N$ -dimensional SEIRD-characteristic vectors

$$\mathbf{p}_X(t) = (p_{X,1}(t), \dots, p_{X,N}(t)) \quad (9)$$

343 for all characteristics  $X \in \{S, E, I, R, D\}$ . The precise diffusion dynamics

---

<sup>5</sup>The Service Level in a supply chain is linked to the proportion of time nodes spend in the Recovered and Susceptible states, indicating their normal functioning ability. Alternatively, the Service Level of a supply chain over a period  $T$  and with nodes in the subset  $V_{SC}$ , can be calculated as the average R+S probability, given by:  $SL_{V_{SC}}(T) = \frac{1}{|V_{SC}|} \sum_{k \in V_{SC}} \frac{1}{T} \int_0^T p_{R_k}(t) dt$  Within the time range of an epidemic wave, a chosen period of the operational cycle  $T$  may not monitor the worst impact of the epidemic.

344 of the disease over the network follows governing equations for the vectors  
 345  $\mathbf{p}_X(t)$ . The details of this dynamical system are explained in [Appendix B](#),  
 346 and have been reported and tested in our studies ([Broekaert et al., 2024b,c](#),  
 347 [2022](#)).

348 Three consecutive epidemic waves are considered, each characterized  
 349 by different infectivity rates ( $\beta_{Med.} \rightarrow \beta_{High} \rightarrow \beta_{Low}$ ) and varying asym-  
 350 metric numbers of infectious seeds. This approach simplifies the formal  
 351 representation of the SEIRSD model by encompassing all infected individu-  
 352 als in a single category  $I$ , rather than tracking each across multiple waves.  
 353 The transition between epidemic waves is maintained within the original  
 354 five-dimensional SEIRD-state by fractionally reassigning each category and  
 reseeding infections.

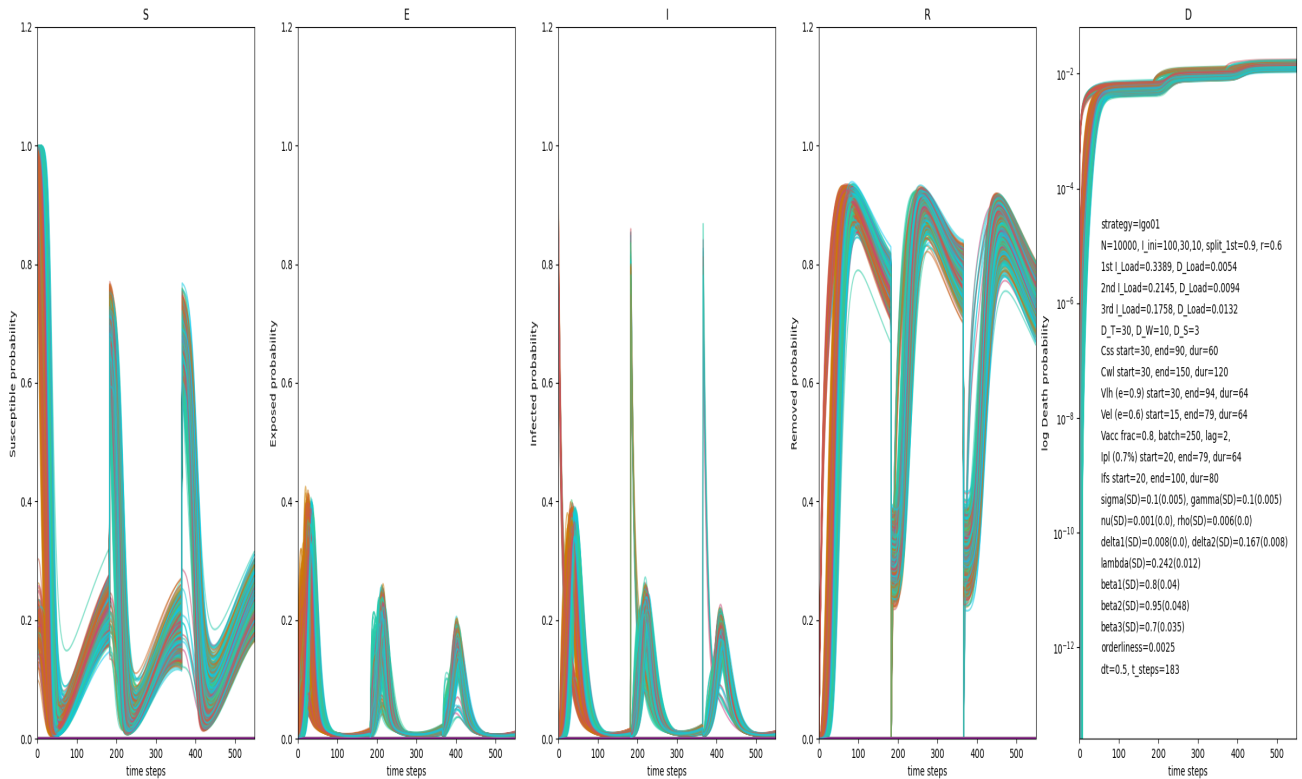


Figure 2: Three consecutive epidemic waves in an uncontrolled SEIRSD epidemic on a designed contact network. The ‘Susceptible’, ‘Exposed’, ‘Infectious’, ‘Recovered’, and ‘Dead’ probabilities are shown for each node in the consecutive panels. (orange hues for group\_0 and blue hues for group\_1)

355 **SC under epidemic controls** Subsequent epidemic waves are initialized  
 356 using the Igo<sub>01</sub> isolation outcome-state, or ‘none\_0 none\_1’ profile, repre-  
 357 senting the worst-case scenario of an uncontrolled epidemic. Given the  
 358 number of possible control policy chains  $(3 \times 9 \times 9)^3$  and the rescaling and  
 359 reseedling method, a sufficient trace of inheritance is retained by defaulting  
 360 to the Igo<sub>01</sub> outcome. Country isolation policies such as Ifs<sub>01</sub> and Ipl<sub>01</sub> may  
 361

362 offer effective control under important asymmetric seeding of the initial  
363 infection.

364 Our study's primary goal is to assess supply chains' resilience and viabil-  
365 ity through SEIRD-based metrics. Supply chains in the multiplex network  
366 are configured by randomly selecting  $l_{SC} = 100$  nodes into a co-activity  
367 unit, avoiding bias in the results.<sup>6</sup> To evaluate the effect of competing epi-  
368 demic control policies on supply chain resilience and viability, the spread  
369 of supply chain nodes across two regions (populations) is varied. Our  
370 model considers five supranational spreads of the supply chains, *spread*  
371 *value*  $\in (0, .25, .5, .75, 1)$ , representing different fractions of nodes distributed  
372 in *population\_0* and complementarily in *population\_1*.

373 In addition to confinement strategies, our model now includes isolation  
374 strategies that reduce or cut social contact between the two groups. This  
375 'frontier closing' control can implemented with three pre-defined isolation  
376 amplitudes: i) no limitations on foreign contacts or, '*freely go*' ( $I_{go_{01}}$ ), ii) a  
377 limitation to only essential cross-border contacts over a longer period, i.e.  
378 '*partial longer isolation*' ( $I_{pl_{01}}$ ), and iii) a total cut-off of all foreign contacts  
379 over a limited period, i.e. '*full but short isolation*' ( $I_{fs_{01}}$ ). These isolation  
380 controls augment the previously implemented strategies: 'none', strict short  
381 or weak long confinement ( $C_{sl}$  and  $C_{wl}$ ), and early less effective or late  
382 highly effective vaccination ( $V_{el}$  or  $V_{lh}$ ), and their combinations. Since  
383 isolation control is mutual between regions, the game matrix reduces to  
384 three matrices of size  $9 \times 9$ . To reduce the concomitant complexity of possible  
385 parametrizations, we implement two basic contact confinement strategies  
386 '*strict isolation & short duration*' ( $C_{ss}$ ) versus '*weak isolation & long duration*'  
387 ( $C_{wl}$ ), and two basic vaccination strategies '*early deployment & lower-efficacy*  
388 *vaccination*' ( $V_{el}$ ) versus '*later deployment & higher-efficacy vaccination*' ( $V_{lh}$ ),  
389 or any possible hybrid of both, or none, of the confinement and vaccination  
390 strategies. (the parameters of the strategies are provided in experimental  
391 Section 5). Considering the availability of each control strategy, separately or  
392 combined, and considering the default or 'no-control'-option, nine possible

---

<sup>6</sup>In real-world situations the historic emergence of supply chains is based on cost and time optimization, production and stock effectivity, trust, and business acumen.

393 strategies, can be enumerated and can be deployed by each sub-population,

$$CS = \begin{bmatrix} \text{none} \\ C_{ss} \\ C_{wl} \end{bmatrix} \otimes \begin{bmatrix} \text{none} \\ \text{Vel} \\ \text{Vlh} \end{bmatrix} \otimes \begin{bmatrix} I_{g01} \\ I_{fs01} \\ I_{pl01} \end{bmatrix} \quad (10)$$

394 and are kept fixed in the reported (*ad hoc*) order for identification in the  
 395 game matrices. The three *isolation* strategies can only be deployed sym-  
 396 metrically between the two policymakers. Besides an insight into a purely  
 397 epidemic mitigation, the crossing of control strategies in this setting leads  
 398 to  $3 \times 9 \times 9$  *Epidemic Control Cost* expressions for each subpopulation. The  
 399 shorthand notation for strategy profiles derived from Eq. (10) enable to  
 400 quickly identify what health measures are deployed by whom. A con-  
 401 finement type starts with C, vaccination with V and isolation type with I.  
 402 Indices 0 or 1 indicate whether a health measure is deployed for individuals  
 403 under the policymaker from ‘country 0’ or ‘country 1’. In the short hand  
 404 notation the health measure by policymaker 0 (1) appear to the left (right).  
 405 The isolation measures always carry an index 01 as these are deployed  
 406 symmetrical by definition and these always appear at the end of the short  
 407 hand notation. For example, the strategy profile  $C_{ss0\_Vel0\_C_{wl1\_Vel1\_I_{fs01}}$   
 408 implies policymaker 0 specifically deploys a ‘strict and short’ confinement  
 409 and an ‘early and with lower efficacy’ vaccination, while policymaker 1  
 410 specifically deploys a ‘weak and long’ confinement and also the ‘early and  
 411 with lower efficacy’ vaccination. Besides, both policymakers also deploy the  
 412 country ‘full and short’ isolation. The specific parametrization of the control  
 413 strategies depends on the longitudinal development and the magnitude  
 414 of the uncontrolled epidemic. The effectiveness of a deployed epidemic  
 415 control strategy will always be assessed relative to the cost and impact of  
 416 the uncontrolled epidemic, i.e.  $I_{g01}$  in terms of the listed strategies Eq.(10).

417 The epidemic evolution is guided by policymakers’ control policies. The  
 418 optimal strategic profile, derived from the cost-based Nash Equilibrium  
 419 in the game matrix, provides a reference point for supply chain managers  
 420 for further planning. A manager’s perspective on supply chain resilience  
 421 may lead to different insights into the best control profile and supply chain  
 422 spread. Our model derives the Nash equilibrium for TTR for each epidemic  
 423 wave and supply chain *spread value* assessing convergences and divergences  
 424 between policymaker and supply chain manager resilience-based perspec-  
 425 tives.

426 Supply chain viability is monitored through the harmonic mean activity,  
 427 or LSL, over the three epidemic waves. A critical assessment is made of the  
 428 repercussions of policymakers' control policies on supply chain viability,  
 429 considering their different international structures.

430  
 431 **Epidemic Control Cost - Using SEIRD-loads for ECC.** Our study aims  
 432 to compare the cost-optimal control policies for two inter-dependent regions  
 433 with strategic profiles that emerge from optimizing resilience and viability of  
 434 supply chains. The Epidemic Control Cost compounds the cost of epidemic  
 435 health policy, the control strategy, and loss of productivity (see [Charpentier](#)  
 436 [et al. \(2020\)](#); [Reddy et al. \(2021\)](#); [Gros et al. \(2021\)](#); [Gollier \(2021\)](#)). The  
 437 epidemic costs are correlated with the severity of the epidemic in various  
 438 ways and will be forecast on epidemic model variables. In contrast with time-  
 439 integrated epidemic characteristics, *SEIRD-loads* capture potential break-  
 440 points as these do not correlate to time-averaged metrics. The policymaker's  
 441 control strategies and their specific parameterization will often depend  
 442 on worst-case scenarios in the longitudinal development of the epidemic  
 443 variables. The *SEIRD-loads* are formalized to capture the *worst impact* of the  
 444 epidemic on a characteristic over the longitudinal time range:

$$X_{\text{load}} = \frac{1}{N} \sum_{j \in V_g} \max_t (p_{X_j}(t)), \quad \forall X \in \{S, E, I, R, D\}. \quad (11)$$

445 The observed and forecast SEIRD-loads, Eq.(11), in each of the populations,  
 446 typically the I-load and D-load, will trigger epidemic containment efforts  
 447 following governmental policy.

448 The policy impact assessment requires that the implemented control strate-  
 449 gies share the exact same underlying reference epidemic and contact net-  
 450 work, while the parameters of the confinement and vaccination modalities  
 451 of a control strategy remain fixed over their various combinations, Eq.(10).  
 452 The detailed expression of the ECC was reported in our studies ([Broekaert](#)  
 453 [et al., 2024c](#)) and in [Appendix C](#). Our model mainly emphasizes four cost  
 454 components related to the epidemic;

- 455 (i) Deployed Control Strategy Costs: This includes the development and  
 456 production of vaccination technology, its deployment, and the im-  
 457 plementation of confinement policies. Costs are influenced by the  
 458 duration and severity of restrictions and are adjusted for GDP differ-

459 ences between countries.

460 (ii) Epidemic-Related Health Policy Deployment Costs: Initially propor-  
461 tional to the infection load, these costs increase when healthcare ca-  
462 pacity is exceeded. The model uses a piecewise linear function to  
463 represent cost transitions, accounting for the expansion of healthcare  
464 facilities and their operational costs.

465 (iii) Value of Human Life (Death Toll): The costs associated with deceased  
466 individuals are proportional to the death count.

467 (iv) Epidemic-Related Loss of Economic Productivity: Using a Cobb-  
468 Douglas production function, the model estimates productivity loss  
469 based on reduced labor force participation due to the epidemic.

470 The SEIRD load-based total incurred epidemic cost,  $ECC_\alpha$  for each sub-  
471 population  $\alpha$  on the graph of two countries  $\alpha \in \{0, 1\}$  is given by

$$ECC_\alpha = c_{cs,\alpha} + c_{I,\alpha} \mathcal{J}(I_\alpha, I_{max\alpha}) + c_{D,\alpha} D_\alpha + c_{L,\alpha} L_{max}^b \left(1 - (1 - E_\alpha - I_\alpha - D_\alpha)^b\right) \quad (12)$$

472 where  $c_{I,\alpha}$  represents the cost of disease-related health policy,  $c_{cs,\alpha}$  is the  
473 implementation cost of the control strategy,  $c_{D,\alpha}$  is the cost of deceased  
474 individuals, and  $c_{L,\alpha}$  is the impact on economic productivity loss.

475 The proportionality factors of cost are expressed relative to annual GDP  
476 per capita following Gros et al. (2021) (Appendix C). The population-  
477 specific implementation cost of their control strategy,  $c_{cs,\alpha} \in \mathbb{R}$ ,  $\alpha \in \{0, 1\}$   
478 and  $cs \in CS$ , is separated along confinement, vaccination and isolation  
479 types and directly summed when strategies are combined. The simula-  
480 tion is implemented for two subpopulations with a GDP difference factor  
481  $(1 - GDP_{diff})$ , where  $GDP_{diff} = .1$ . Subpopulation 1 is the reference, and  
482 subpopulation group-0 is corrected for its limited resources by a factor  
483  $(1 - GDP_{diff})$ . The cost of intervention from the implemented control strat-  
484 egy,  $c_{cs,\alpha}$ , is scaled by  $CS_{scale} = 1.5$ . Based on Gollier (2021), the relative cost  
485  $CV_{ratio}$  of deploying a confinement strategy versus a vaccination strategy  
486  $CV_{ratio} = .1$ , here. The cost correlation factors are taken equal  $c_I = c_L$ .  
487 The parameters of the confinement strategy impact its operation cost. The  
488 relative confinement duration and severity of contact reduction are imple-  
489 mented as proportional factors, with a lower operation cost in the country  
490 with a relatively lower GDP. Formally, the confinement severity is expressed

491 as a relative deviation from the average number of contacts under normal  
492 circumstances without an epidemic in  $c_{C_{SS}}$ ,  $c_{C_{wl}}$ ,  $c_{I_{fs01}}$  and  $c_{I_{pl01}}$ .  
493 The operation and development cost of the vaccination strategy,  $c_{V_{el}}$ ,  $c_{V_{lh}}$ , is  
494 expressed on its time of launch and effectivity. This framework now allows  
495 for the numerical assessment the deployment cost of all crossed control  
496 strategies, purely based on SEIRD-loads. In contrast to an optimization  
497 approach targeting the minimum of the *time-integrated* cost, the identifica-  
498 tion of the optimal strategy results from the Nash equilibrium analysis of  
499 the game matrix of *SEIRD load-based* costs for all crossed strategies.

#### 500 4. Methodology and simulation algorithms

501 **Formalism.** The simulated network is conceived as a contact graph  
502  $\mathcal{G}(V_g, E_g)$  spanned on  $N = 10^4$  nodes of  $V_g$  and with dynamical adjacency,  
503 which enables the diffusion of the disease across all contacts  $E_g$ . Both  
504 the specific topology of the social contact network ([Appendix A](#)) and  
505 the probabilistic SEIRSD evolution ([Appendix B](#)) have been modeled to  
506 reflect real-world contact structure ([Barrett et al., 2009](#)) and COVID-19  
507 parametrization ([Broekaert et al., 2024c](#)). From a technical perspective,  
508 several modifications have been made to the model. An adjacency algo-  
509 rithm based on contact probability exponential decay is implemented to  
510 realistically simulate contact networks, allowing for large networks. A faster  
511 time pace of epidemic evolution ( $dt = .5$ ) is used, reducing computation  
512 time without sacrificing accuracy. Following input initialization for each  
513 control configuration, the main algorithm is the Euler-forward method to  
514 numerically solve the coupled ODE system, Eqs. ([B.1](#)), by using an updated  
515 infinitesimal propagator with each time increment, see [Fig. 3](#). Over three  
516 epidemic waves, the resulting SEIRD-histories ( $3 \times 3 \times 9 \times 9$ ) then serve  
517 to obtain the SEIRD-loads and activity histories of all supply chains with  
518 different spreading over the two populations. These allow to calculate the  
519 ECC, TTR and LSL following which their Nash equilibria strategy profiles  
520 can be obtained.

521 **Epidemic wave sequence** At the onset of each new wave, all node states  
522 are re-evaluated concerning the new virus variant. The transitions between

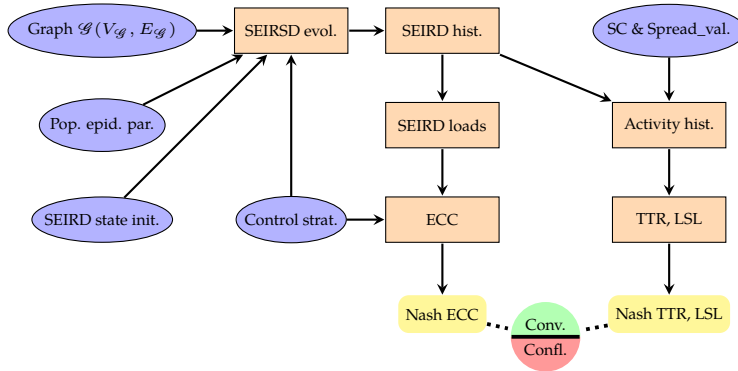


Figure 3: Formal flow of algorithms and methods to analyze conflicts and convergences in epidemic control policies for ECC and resilience and viability of supply chains.

523 waves are formalized according to the single-time step evolution:

$$\Pi_k(T + dt) = (1 - V_{I_k}) \begin{bmatrix} p_{S_k} + r_k(p_{E_k} + p_{I_k} + p_{R_k}) \\ (1 - r_k)p_{E_k} \\ (1 - r_k)p_{I_k} \\ (1 - r_k)p_{R_k} \\ p_{D_k} \end{bmatrix}_{(T)} + V_{I_k} \begin{bmatrix} (1 - r_I) - p_{D_k} \\ 0 \\ r_I \\ 0 \\ p_{D_k} \end{bmatrix}_{(T)} \quad (13)$$

where  $V_I$  is a random vector indicating infection seeds (0 or 1) with a fixed number and (as)symmetry,  $r_I$  is the infection probability of the seed, and  $(p_{S_k}, p_{E_k}, p_{I_k}, p_{R_k}, p_{D_k})_{(T)}$  is the output state vector of node  $k$  from the previous wave under the 'Igo<sub>01</sub>' control. Nodes in the population evolve by inheriting scaled characteristics or by seeding with the new virus in limited cases. Recovered individuals become largely susceptible again, with a fraction  $r_k$  (e.g., 70%) of  $p_{R_k}$  pooled back with  $p_{S_k}$  for each node  $k$ . The value  $r_k$  is sampled from a truncated normal distribution for each node. Exposed and infected characteristics are similarly reduced and pooled with  $S$ , renewing sensitivity to the new virus. The number of infective seeds changes over the waves, 100 in the first, 30 in the second, and 10 in the third, reflecting the unexpected nature of the first wave and improved anticipation in subsequent waves. Seeding initially occurs asymmetrically to suggest a dominant source in only one of the populations. The Dead characteristic remains an absorbing state, with  $p_D$  invariant during new virus introductions.

**Vaccination** In our present model, the vaccination state vector is implemented according to:

$$\Pi_k(t + dt) = (1 - e) \Pi_k(t) + e (0, 0, 0, 1 - p_{D_k}(t), p_{D_k}(t)).$$

524 This equation weights the successful vaccination outcome state with effi-  
 525 ciency  $e$  and retains the old node state vector with weight  $(1 - e)$ .

526 Finally, our model applies truncated normal distributions to all demo-  
 527 graphic parameters, including  $r_k$ , the reset parameter of the SEIRD node-  
 528 state at the start of the next epidemic wave, and  $r_{I_k}$ , the infection rate of the  
 529 infected seeds causing the next wave.

530 **Model parametrization** The numerical simulation entails fixing parameters  
 531 in the various inputs of the model identified in Fig. 3. The parameter values  
 are listed in Table 1.

Table 1: Model parameter values for the numerical simulation.

<b>Epidemic Parameters</b>	init_infected_1 = 100, init_infected_2 = 30, init_infected_3 = 10, ini_rate = 0.8, split_infect = 0.9, beta_bulk_1 = 0.8, beta_bulk_2 = 0.95, beta_bulk_3 = 0.7, delta1 = epsilon * 1/4, delta2 = 1/6, lambdal = (1 - epsilon) * 1/4, nu = 0.001, rho = 1/180, gamma_bulk = 0.1, sigmas_bulk = 0.1, SDfrac = 0.05, r = 0.6, epsilon = 0.03
<b>Adjacency Parameters</b>	D_T = 30, D_W = 10, D_S = 3, D_eow = 60, pMid = 0.5, pEnd = 0.95, weight = 0.9, orderliness = 0.0025
<b>Confinement Parameters</b>	start_C = 30 / (2 * dt), start_Css = start_C, start_Cwl = start_C, dur_Css = 60 / (2 * dt), dur_Cwl = 120 / (2 * dt), end_Css = start_Css + dur_Css, end_Cwl = start_Css + dur_Cwl
<b>Isolation Parameters</b>	frac_isol = 0.7, start_Ifs = 20 / (2 * dt), start_Ipl = 10 / (2 * dt), dur_Ifs = 80 / (2 * dt), dur_Ipl = 160 / (2 * dt), end_Ifs = start_Ifs + dur_Ifs, end_Ipl = start_Ipl + dur_Ipl
<b>Vaccination Parameters</b>	fraction_vaccinated = 0.8, start_Vel = 15 / (2 * dt), start_Vlh = 30 / (2 * dt), vacc_batch = 0.05 * N / 2, steps_lag_V = 4 * dt, steps_lag_Vel = steps_lag_V, steps_lag_Vlh = steps_lag_V, e_Vel = 0.6, e_Vlh = 0.9
<b>Time Parameters</b>	dt = 0.5, T_start = 0, T_end = 365 / (4 * dt)
<b>Cost Parameters</b>	GDP_diff = 0.1, CS_scale = 1.5, conf_vacc_ratio = .1, scaleC = conf_vacc_ratio * CS_scale, scaleV = CS_scale
<b>Supply Chain Par's</b>	l <sub>SC</sub> = 100, N <sub>SC</sub> = 10, spread_value ∈ {0, .25, .5, .75, 1}
<b>LSL Parameters</b>	perf_thresh = 0.7

532

## 533 5. Simulation results and discussion

534 Given their differing objectives, policymakers and supply chain man-  
 535 agers exhibit both convergences and conflicts in their choice of optimal

536 control policies. A comparative analysis of the Nash equilibria based on  
 537 Epidemic Control Cost (Table 2), TTR (Table 3), and LSL (Table 4) de-  
 538 rived from the simulation experiment leads to the following observations.  
 Various conditions of *wave* and *spread value* let multiple Nash equilibria

Epidemic Control Cost			( 'lower is better' )
Epidemic wave	Isolation strategy	Nash profile policymakers 0 vs. 1	Nash equilibria values 0 vs. 1
first	<b>Igo<sub>01</sub></b> *	Css <sub>1</sub> _Vel <sub>1</sub> , Cwl <sub>0</sub> _Vel <sub>0</sub> _Css <sub>1</sub> _Vel <sub>1</sub> *	[0.225, 0.205], [ <b>0.225, 0.202</b> ]*
	Ifs <sub>01</sub>	Css <sub>0</sub> _Vel <sub>0</sub> _Cwl <sub>1</sub> _Vel <sub>1</sub>	[0.282, 0.246]
	Ipl <sub>01</sub>	Css <sub>1</sub> _Vel <sub>1</sub> , Cwl <sub>0</sub> _Vel <sub>0</sub> _Css <sub>1</sub> _Vel <sub>1</sub>	[0.287, 0.273], [0.287, 0.271]
second	<b>Igo<sub>01</sub></b> *	<b>none</b> *	[ <b>0.274, 0.304</b> ]*
	Ifs <sub>01</sub>	Cwl <sub>1</sub> _Vel <sub>1</sub>	[0.334, 0.368]
	Ipl <sub>01</sub>	none	[0.336, 0.373]
third	<b>Igo<sub>01</sub></b> *	Css <sub>0</sub> _Css <sub>1</sub> , Css <sub>0</sub> _Css <sub>1</sub> _Vel <sub>1</sub> *	[0.343, 0.381], [ <b>0.342, 0.381</b> ]*
	Ifs <sub>01</sub>	Css <sub>0</sub> _Css <sub>1</sub>	[0.404, 0.449]
	Ipl <sub>01</sub>	Css <sub>0</sub> _Css <sub>1</sub>	[0.404, 0.449]

Table 2: Policy maker’s strategic control Nash equilibria based on Epidemic Control Cost, for consecutive epidemic waves.

539 profiles occur based on ECC, TTR or LSL. In a two-player zero-sum game,  
 540 the payoff of the first player is the negative of the payoff of the second player.  
 541 In contrast, a non-zero-sum game, as exemplified in our current model, can  
 542 yield multiple Nash equilibria due to the dissimilar bimatrix payoffs. The  
 543 study by (Punniyamorthy et al., 2023) proposes multi-criteria methods  
 544 to select an optimal Nash equilibrium when multiple options are available.  
 545 In this case, a heuristic is applied here which selects the *improved values for*  
 546 *both players*.

548 **Initial observations** reveal that the Nash ECC rises over the consecutive  
 549 epidemic waves, and tends to be lower for region\_0 compared to region\_1 –  
 550 except during the first one, Table 2. This trend aligns with the accumulated  
 551 death toll (D), while the latter exception is attributed to the initial asymmet-  
 552 rical and dominant infection seeding in region\_0 during the first wave (see  
 553 Table 1). In the first wave, the Nash profile suggests a vaccination campaign  
 554 – **Vel** in both regions. However, in the second and third waves, driven by new  
 555 viral strains, policymakers largely abandon vaccination efforts, except in  
 556 economically stronger region\_1 during the third wave (Vel<sub>1</sub>). Throughout  
 557 all waves, policymakers opt against restricting inter-regional contacts. In  
 558 stark contrast, supply chain managers prioritize maintaining competitive  
 559 TTR and LSL, leading them to prefer isolating contacts between the two

Time To Recovery			( 'lower is better' )	
Wave	Spread value	Isolation	Nash profile SC managers 0 & 1	Nash values 0 & 1
first	0.00	Igo <sub>01</sub> *	Css <sub>0</sub> _Vel <sub>0</sub> _Cwl <sub>1</sub> _Vel <sub>1</sub> *	[35.7, 33.0] *
		Ifs <sub>01</sub>	Css <sub>0</sub> _Vel <sub>0</sub> _Cwl <sub>1</sub> _Vlh <sub>1</sub> , ...	[42.0, 32.5], ...
		Ipl <sub>01</sub> *	Css <sub>0</sub> _Vel <sub>0</sub> _Cwl <sub>1</sub> _Vel <sub>1</sub> *	[35.7, 33.0] *
	0.25	Igo <sub>01</sub>	Css <sub>0</sub> _Vel <sub>0</sub> _Cwl <sub>1</sub> _Vel <sub>1</sub> , Vel <sub>0</sub> _Css <sub>1</sub> _Vel <sub>1</sub>	[35.9, 34.0], [37.2, 35.2]
		Ifs <sub>01</sub> *	Cwl <sub>0</sub> _Vel <sub>0</sub> _Cwl <sub>1</sub> _Vel <sub>1</sub> *	[35.2, 34.0] *
		Ipl <sub>01</sub>	Css <sub>0</sub> _Vel <sub>0</sub> _Cwl <sub>1</sub> _Vel <sub>1</sub> , Vel <sub>0</sub> _Css <sub>1</sub> _Vel <sub>1</sub>	[35.9, 34.0], [37.2, 35.2]
	0.50	Igo <sub>01</sub>	Css <sub>0</sub> _Vel <sub>0</sub> _Cwl <sub>1</sub> _Vel <sub>1</sub>	[34.7, 34.7]
		Ifs <sub>01</sub> *	Css <sub>0</sub> _Vel <sub>0</sub> _Cwl <sub>1</sub> _Vel <sub>1</sub> *	[34.0, 34.0] *
		Ipl <sub>01</sub>	Css <sub>0</sub> _Vel <sub>0</sub> _Cwl <sub>1</sub> _Vel <sub>1</sub>	[34.7, 34.7]
	0.75	Igo <sub>01</sub>	Css <sub>0</sub> _Vel <sub>0</sub> _Cwl <sub>1</sub> _Vel <sub>1</sub>	[34.0, 35.9]
		Ifs <sub>01</sub> *	Css <sub>0</sub> _Vel <sub>0</sub> _Cwl <sub>1</sub> _Vel <sub>1</sub> *	[33.9, 35.3] *
		Ipl <sub>01</sub>	Css <sub>0</sub> _Vel <sub>0</sub> _Cwl <sub>1</sub> _Vel <sub>1</sub>	[34.0, 35.9]
1.00	Igo <sub>01</sub>	Css <sub>0</sub> _Vel <sub>0</sub> _Cwl <sub>1</sub> _Vel <sub>1</sub>	[33.0, 35.7]	
	Ifs <sub>01</sub> *	Css <sub>0</sub> _Vel <sub>0</sub> _Cwl <sub>1</sub> _Vel <sub>1</sub> *	[32.7, 35.0] *	
	Ipl <sub>01</sub>	Css <sub>0</sub> _Vel <sub>0</sub> _Cwl <sub>1</sub> _Vel <sub>1</sub>	[33.0, 35.7]	
second	0.00	Igo <sub>01</sub>	Vlh <sub>0</sub> _Css <sub>1</sub> _Vel <sub>1</sub> , Css <sub>0</sub> _Vel <sub>0</sub> _Css <sub>1</sub> _Vlh <sub>1</sub>	[30.7, 41.6], [33.9, 30.2]
		Ifs <sub>01</sub> *	Cwl <sub>0</sub> _Vel <sub>0</sub> _Cwl <sub>1</sub> _Vel <sub>1</sub> *, ...	[30.1, 30.0] *, ...
		Ipl <sub>01</sub>	Vlh <sub>0</sub> _Css <sub>1</sub> _Vel <sub>1</sub> , Css <sub>0</sub> _Vel <sub>0</sub> _Css <sub>1</sub> _Vlh <sub>1</sub>	[30.7, 41.6], [33.9, 30.2]
	0.25	Igo <sub>01</sub>	Css <sub>0</sub> _Vel <sub>0</sub> _Cwl <sub>1</sub> _Vel <sub>1</sub>	[31.0, 30.7]
		Ifs <sub>01</sub> *	Cwl <sub>0</sub> _Vel <sub>0</sub> _Cwl <sub>1</sub> _Vel <sub>1</sub> *	[30.6, 30.6] *
		Ipl <sub>01</sub>	Css <sub>0</sub> _Vel <sub>0</sub> _Cwl <sub>1</sub> _Vel <sub>1</sub>	[31.0, 30.7]
	0.50	Igo <sub>01</sub>	Css <sub>0</sub> _Vel <sub>0</sub> _Cwl <sub>1</sub> _Vel <sub>1</sub>	[30.7, 30.7]
		Ifs <sub>01</sub> *	Css <sub>0</sub> _Vel <sub>0</sub> _Cwl <sub>1</sub> _Vel <sub>1</sub> *	[30.5, 30.5] *
		Ipl <sub>01</sub>	Css <sub>0</sub> _Vel <sub>0</sub> _Cwl <sub>1</sub> _Vel <sub>1</sub>	[30.7, 30.7]
	0.75	Igo <sub>01</sub>	Css <sub>0</sub> _Vel <sub>0</sub> _Cwl <sub>1</sub> _Vel <sub>1</sub>	[30.7, 31.0]
		Ifs <sub>01</sub> *	Css <sub>0</sub> _Vel <sub>0</sub> _Cwl <sub>1</sub> _Vel <sub>1</sub> *	[30.2, 31.0] *
		Ipl <sub>01</sub>	Css <sub>0</sub> _Vel <sub>0</sub> _Cwl <sub>1</sub> _Vel <sub>1</sub>	[30.7, 31.0]
1.00	Igo <sub>01</sub>	Css <sub>0</sub> _Vel <sub>0</sub> _Cwl <sub>1</sub> _Vel <sub>1</sub>	[30.4, 30.7]	
	Ifs <sub>01</sub> *	Cwl <sub>0</sub> _Vel <sub>0</sub> _Cwl <sub>1</sub> _Vel <sub>1</sub> *	[30.0, 30.1] *	
	Ipl <sub>01</sub>	Css <sub>0</sub> _Vel <sub>0</sub> _Cwl <sub>1</sub> _Vel <sub>1</sub>	[30.4, 30.7]	
third	0.00	Igo <sub>01</sub>	Css <sub>0</sub> _Vel <sub>0</sub> _Cwl <sub>1</sub> _Vlh <sub>1</sub> , Cwl <sub>0</sub> _Vlh <sub>0</sub> _Css <sub>1</sub> _Vel <sub>1</sub>	[32.2, 29.0], [28.8, 32.1]
		Ifs <sub>01</sub> *	Cwl <sub>0</sub> _Vel <sub>0</sub> _Css <sub>1</sub> _Vlh <sub>1</sub> *, ...	[30.9, 28.7] *, ...
		Ipl <sub>01</sub>	Css <sub>0</sub> _Vel <sub>0</sub> _Cwl <sub>1</sub> _Vlh <sub>1</sub> , Cwl <sub>0</sub> _Vlh <sub>0</sub> _Css <sub>1</sub> _Vel <sub>1</sub>	[32.2, 29.0], [28.8, 32.1]
	0.25	Igo <sub>01</sub>	Css <sub>0</sub> _Vel <sub>0</sub> _Cwl <sub>1</sub> _Vel <sub>1</sub> , Cwl <sub>0</sub> _Vel <sub>0</sub> _Css <sub>1</sub> _Vel <sub>1</sub>	[29.5, 29.5], [29.3, 29.5]
		Ifs <sub>01</sub> *	Cwl <sub>0</sub> _Vel <sub>0</sub> _Css <sub>1</sub> _Vel <sub>1</sub> *	[29.0, 29.2] *
		Ipl <sub>01</sub>	Css <sub>0</sub> _Vel <sub>0</sub> _Cwl <sub>1</sub> _Vel <sub>1</sub> , Cwl <sub>0</sub> _Vel <sub>0</sub> _Css <sub>1</sub> _Vel <sub>1</sub>	[29.5, 29.5], [29.3, 29.5]
	0.50	Igo <sub>01</sub>	Css <sub>0</sub> _Vel <sub>0</sub> _Cwl <sub>1</sub> _Vel <sub>1</sub> , Cwl <sub>0</sub> _Vel <sub>0</sub> _Css <sub>1</sub> _Vel <sub>1</sub>	[29.4, 29.4], [29.4, 29.4]
		Ifs <sub>01</sub> *	Cwl <sub>0</sub> _Vel <sub>0</sub> _Cwl <sub>1</sub> _Vel <sub>1</sub> *	[29.1, 29.1] *
		Ipl <sub>01</sub>	Css <sub>0</sub> _Vel <sub>0</sub> _Cwl <sub>1</sub> _Vel <sub>1</sub> , Cwl <sub>0</sub> _Vel <sub>0</sub> _Css <sub>1</sub> _Vel <sub>1</sub>	[29.4, 29.4], [29.4, 29.4]
	0.75	Igo <sub>01</sub>	Css <sub>0</sub> _Vel <sub>0</sub> _Css <sub>1</sub> _Vel <sub>1</sub>	[29.5, 29.4]
		Ifs <sub>01</sub> *	Cwl <sub>0</sub> _Vel <sub>0</sub> _Css <sub>1</sub> _Vel <sub>1</sub> *	[29.2, 29.0] *
		Ipl <sub>01</sub>	Css <sub>0</sub> _Vel <sub>0</sub> _Css <sub>1</sub> _Vel <sub>1</sub>	[29.5, 29.4]
1.00	Igo <sub>01</sub>	Css <sub>0</sub> _Vel <sub>0</sub> _Css <sub>1</sub> _Vel <sub>1</sub>	[29.1, 29.1]	
	Ifs <sub>01</sub> *	Cwl <sub>0</sub> _Vel <sub>0</sub> _Css <sub>1</sub> _Vel <sub>1</sub> *	[28.8, 28.7] *	
	Ipl <sub>01</sub>	Css <sub>0</sub> _Vel <sub>0</sub> _Css <sub>1</sub> _Vel <sub>1</sub>	[29.1, 29.1]	

Table 3: Manager's strategic control Nash Equilibria based on Time To Recovery (TTR) to regain an activity threshold of .70, for epidemic waves and possible supply chain spread over the two populations (Spread Value).

560 regions ( $\mathbf{I}fs_{01}$ ).<sup>7</sup>

561 the supply chain's TTR-based Nash strategy successfully reduces recov-  
562 ery time across epidemic waves by selecting control profiles that sustain  
563 higher activity levels of the nodes. Despite the increased infectiousness of  
564  $\beta_2$ , but fewer infectious seeds, a full outbreak of the epidemic is mitigated.  
565 For the interpretation of the supply chain's LSL-based Nash profiles for  
566 different spread values one needs to read the entries according to comple-  
567 mentary spreading for region\_0 and region\_1. This implies that region\_0's  
568 supply chain with *spread value* = *val* competes with region\_1's supply chain  
569 with *spread value* =  $1 - val$ .

570 The LSL Nash for *spread value*=0 shows a high LSL=.763 for a supply chain  
571 fully in region\_1, and a lower LSL=.675 for a supply chain fully in region\_0.  
572 Clearly, in the case of supply chains fully contained in one region, the LSL is  
573 sensitive to the impact of the first wave that -by design- dominantly struck  
574 region\_0. In contrast, supply chains with a balanced spread of .5 over both  
575 regions reach an LSL Nash of .722 each, showing the advantage of risk  
576 spreading by delocalising supply chain nodes.

577 By comparing the Nash equilibria in Tables 2 (ECC), 3 (TTR, and 4  
578 (LSL), several conflicts and convergences between the policy makers (play-  
579 ers 0 and 1) and supply chain managers can be identified.

580 **Control Conflicts:** comparing optimal strategies based on Epidemic Control  
581 Cost and Time To Recovery reveals that policymakers consistently prefer  
582 the  $\mathbf{I}go_{01}$  strategy (2) across waves, while supply chain managers favor  
583  $\mathbf{I}fs_{01}$  isolation (3). Only during the first epidemic wave, when seeding is  
584 asymmetric in group\_0, does a Spread Value zero supply chain manager  
585 -i.e. fully active in group 1- prefer no-isolation strategy or a partial-longer  
586 one ( $\mathbf{I}pl_{01}$ ). Furthermore, comparing ECC-based strategies with LSL-based  
587 ones shows, across all waves, that the policymakers' preferred isolation  
588 strategy ( $\mathbf{I}go_{01}$ ) does not align with those maximizing LSL for supply chain

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<sup>7</sup>The only exception to this general preference for  $\mathbf{I}fs_{01}$  is during the *first* wave and uniquely for SC with *spread\_value* = 0, hence fully located in region\_1, in which case the TTR-based Nash prescribes  $\mathbf{I}go_{01}$  or  $\mathbf{I}pl_{01}$  with both delivering the numerically same outcome. Due to the high asymmetry of infectious seeding during wave one in region\_0 the *isolation* may play no role on the TTR of the SC fully concentrated in region\_0, while it would for degrading those in region\_1. (Note that the LSL-based Nash does not show this discrepancy, because the previous effect is harmonically averaged out over consecutive waves.)

589 managers,  $I_{fs01}$  consistently renders higher LSL across various Spread Val-  
 590 ues. All TTR and LSL Nash equilibria invoke four control components  
 591 -a confinement and vaccination variant for each group- and an isolation  
 592 strategy: the implementation cost of the policies tends to tone down the  
 593 approach of the policymaker's ECC Nash equilibria.

**Control Convergences:** In the first wave's asymmetric configuration, sup-

Longitudinal Service Level			( 'higher is better' )
Spread Value	Isolation Type	Nash profile SC managers 0 & 1	Nash values 0 & 1
0.00	$I_{g01}$	Css0_Vel0_Css1_Vel1	[0.759, 0.657]
		Vlh1	[0.579, 0.532]
	$I_{fs01}^*$	Cwl0_Cwl1	[0.540, 0.544]
		Vlh0	[0.543, 0.543]
		Vlh0_Vlh1	[0.579, 0.543]
		<b>Css0_Vel0_Cwl1_Vel1*</b>	<b>[0.763, 0.675]*</b>
$I_{pl01}$	Css0_Vel0_Css1_Vel1	[0.759, 0.657]	
0.25	$I_{g01}$	Css0_Vel0_Css1_Vel1	[0.729, 0.667]
	$I_{fs01}^*$	<b>Css0_Vel0_Css1_Vel1*</b>	<b>[0.755, 0.683]*</b>
	$I_{pl01}$	Css0_Vel0_Css1_Vel1	[0.730, 0.667]
0.50	$I_{g01}$	Css0_Vel0_Css1_Vel1	[0.701, 0.701]
	$I_{fs01}^*$	<b>Css0_Vel0_Css1_Vel1*</b>	<b>[0.722, 0.722]*</b>
	$I_{pl01}$	Css0_Vel0_Css1_Vel1	[0.701, 0.701]
0.75	$I_{g01}$	Css0_Vel0_Css1_Vel1	[0.667, 0.729]
	$I_{fs01}^*$	<b>Css0_Vel0_Css1_Vel1*</b>	<b>[0.683, 0.755]*</b>
	$I_{pl01}$	Css0_Vel0_Css1_Vel1	[0.667, 0.730]
1.00	$I_{g01}$	Css0_Vel0_Css1_Vel1	[0.657, 0.759]
	$I_{fs01}^*$	<b>Css0_Vel0_Css1_Vel1*</b>	<b>[0.674, 0.788]*</b>
	$I_{pl01}$	Css0_Vel0_Css1_Vel1	[0.657, 0.759]

Table 4: Manager's strategic control Nash Equilibria based on Longitudinal Service Level (LSL), averaged over consecutive epidemic waves and for various spreading of the supply chains over the two regions (Spread Value).

594 ply chains with Spread Value = 0 convergence on the  $I_{g01}$  strategy, aligning  
 595 policymakers with supply chain managers aiming for lower TTR.  
 596 In the epidemically weaker third wave, for balanced supply chains (Spread  
 597 Value = 0.5) both policymakers and supply chain managers again converge  
 598 on the  $I_{g01}$  strategy. Clearly, a control conflict between policymaker's and  
 599 supply chain manager's preferred policies appears in the deployment of  
 600 confinement and vaccination policies. The increased cost implications of  
 601 deploying vaccination consistently contrast with the TTR-based and LSL-  
 602 based benefits for the performance of the supply chains. Specifically for  
 603 region\_0 with lower GDP, the vaccination control is only applied in the  
 604 worst epidemic wave (first wave). Also on the use of the confinement con-  
 605

606 trol policy, some conflicts between both perspectives arise during the second  
607 epidemic wave: EEC-based no controls are ordained, while a TTR-aimed  
608 control would deploy some confinement measures in both regions.

609 **Effect of Spread Value on Conflicts and Convergences.** For Spread  
610 Value = 0, the supply chains fully controlled by region\_1 show some align-  
611 ment in the first wave but diverge in subsequent waves as managers prefer  
612  $I_{fs_{01}}$  strategies for lower TTR and higher LSL. The Spread Value = 1, with  
613 supply chains fully controlled by region\_0, similarly shows initial alignment  
614 in the first wave but conflicting approaches in later epidemic waves. For  
615 the intermediate Spread Value = 0.50, a full strategic *symmetry* occurs for  
616 the ECC and TTR equilibria in the third epidemic wave and the LSL Nash  
617 equilibrium. While the precise strategic profile is not the same in each case  
618 (ECC, TTR or LSL), the symmetry of the control approach may foster syn-  
619 ergetic deployments in both groups and implicitly commends the balanced  
620 risk spreading in the supply chain location.

621 In summary, the Spread Value significantly affects conflict or conver-  
622 gence between policymakers and supply chain managers. Fully controlled  
623 supply chains (Spread Value = 0 or 1) exhibit clearer conflict patterns, while  
624 intermediate Spread Values introduce a more complex image.

625 Besides the value for the measure of supranational spreading of supply  
626 chains, the economic parameter values in the model determine the ECC, as  
627 shown in [Appendix C](#) and culminating Eq.(12), within Nash profiles and  
628 convergence or divergence of strategies. In our previous work, we pointed  
629 out that an estimate of this variability is obtained from the *ECC-elasticity*  
630 with model parameters ([Broekaert et al., 2024c](#)). While most parameters  
631 exhibit an inelastic effect, a shift in Nash Equilibrium may ensue because  
632 various control combinations can lead to similar ECC values, as shown in  
633 [Table D.5](#).

634 **Practical applicability.** Two case studies from the literature illustrate the  
635 potential application of our model in real-world scenarios. These cases show  
636 how the model can be included to evaluate the resilience of supranational  
637 supply chains during epidemics, demonstrating its relevance to both current  
638 and historical events. By comparing these real cases with the model's  
639 descriptions and predictions, we aim to demonstrate the effectiveness of our  
640 proposed work in guiding decision-making for policymakers and supply  
641 chain managers.

642 *Case Study 1: The Impact of the COVID-19 Pandemic on Food Retail Sup-*  
643 *ply Chains in Germany.* The case study by [Burgos and Ivanov \(2021\)](#) uses

644 a discrete-event simulation model with anyLogistix to analyze how vari-  
645 ous pandemic scenarios affected supply chain operations and resilience. It  
646 identifies critical factors such as pandemic intensity, government lockdown  
647 measures, inventory-ordering dynamics, and shifts in customer behavior.  
648 Notably, demand surges and supplier shutdowns significantly impacted  
649 supply chain performance, while transportation disruptions had a compar-  
650 atively lower effect. The network ontology of this study covers ten product  
651 categories with three suppliers each (totaling 30) which three distribution  
652 centers spread across Germany transport to 28 supermarket locations in five  
653 different countries, Germany, Austria, the Czech Republic, Italy, and Hun-  
654 gary. Our individual-based network model with geographic embedding  
655 could provide complementary factors to the analysis of the performance of  
656 the supranational food retail supply chains. In their ‘Scenario 2’ –which in-  
657 volves a *shutdown at suppliers’ factories* due to labor unavailability– a disease-  
658 based impact over time and per network node in the supply chain could  
659 provide a more detailed variable for local labor availability per site. This  
660 detailed component description could include differing control strategies  
661 in Germany’s neighboring countries and enable comparative performance  
662 analysis of interchanged strands in the supply network.

663 In ‘Scenario 3’, which tests the *bottlenecks due to increased border controls*,  
664 their study analyzes disruptions to the normal flow of goods transported  
665 into the country but does not consider the possible factor of the (partially)  
666 reduced virus spread across the border as suggested by our model ontology.  
667 Conversely, their inclusion of changed consumer behavior in Scenario 1  
668 –such as a +75% *increase in demand* due to panic buying following the first  
669 lockdown, followed by base demand increase of +10%, and +35% for the  
670 second wave– could be incorporated into assessing supply chain efficiency  
671 in our model.

672 *Case Study 2: Supply chain management of online retailer JD.com during*  
673 *COVID-19.* In a case study by [Shen and Sun \(2023\)](#), the authors examine  
674 the impact of the COVID-19 pandemic on supply chain resilience in China,  
675 focusing on JD.com. They use quantitative operational data to highlight  
676 how JD.com adapted its supply chain management in response to excep-  
677 tional demand and logistical disruptions. Key insights reveal that JD.com’s  
678 integrated supply chain structure and intelligent platforms were crucial  
679 for maintaining resilience. The company’s ability to modify delivery proce-  
680 dures and collaborate effectively with various stakeholders –including gov-  
681 ernment and society– provides practical strategies for navigating large-scale

682 disruptions. Policymaker lockdown measures impacted JD.com’s Wuhan  
683 (PRC) distribution center, which serves 120 subordinate warehouses in  
684 Hubei, Hunan, Jiangxi, and Henan provinces. This prompted JD.com to  
685 adapt its functional network and operations. The paralyzed distribution  
686 network in Hubei province led to a real-time data-driven redesign. Un-  
687 available paths and downed distribution centers were removed, optimizing  
688 their supply network based on costs, turnover duration, and sales. Cost-  
689 based reconfigurations of supply chains following control policy-related  
690 losses were proposed using the multiplex network ontology in our study  
691 [Broekaert et al. \(2024c\)](#): the particular adaptations to their configurations  
692 follow the regional control implementations here and provide resilience by  
693 exchanging components.

694 **Model constraints and limitations.** The ontology of our model is a  
695 multiplex network model that integrates social contacts and supply chain  
696 activities. However, these components may not adequately account for  
697 influential agents in a business system during major disruptions, such as  
698 financial markets, investors, or labor migration patterns. Lucas’s critique  
699 should be considered, as real-world variability and uncertainty during ma-  
700 jor disruptions may not align with parameter scaling in the predefined  
701 historical ontology and its dynamics. The model is specifically tailored  
702 for epidemic scenarios and health strategies, requiring adaptation for gen-  
703 eralization to other types of disruptions or specific industries. Only the  
704 most basic configuration of two regions on a static network was covered.  
705 In principle, changing populations with migrations could be considered,  
706 which would require information on the transient parts of the network  
707 structures. Considering more than two regions or policymakers in the con-  
708 figuration requires extending to multi-player matrix games to identify the  
709 Nash equilibrium strategic profile.

710 Additionally, the focus on supranational supply chains may not address  
711 challenges unique to smaller or more localized supply chains. Furthermore,  
712 the longitudinal scope for the LSL metric might not fully capture long-  
713 term impacts on aspects such as employment or consumer behavior shifts  
714 due to prolonged adverse conditions. Our approach primarily involves  
715 mostly static policy analysis, with changes in strategic profiles occurring  
716 only between epidemic waves. In reality, policies are dynamically adjusted  
717 as new information emerges during each epidemic episode. The possibility  
718 of synergetic effects from cooperation is not accounted for in the encom-  
719 passing control costs in our current model. The presented matrix game

720 neither penalizes asymmetric strategic profiles nor rewards symmetric ones.  
721 Synergetic effects from cooperative epidemic control strategies by regional  
722 policymakers can arise from several key factors: information sharing en-  
723 hances the ability to detect and respond to outbreaks collaboratively by  
724 mobilizing joint health supply chains, sharing laboratory facilities, training  
725 institutions, and emergency stockpiles. These factors could be incorporated  
726 by modularly reducing the ECC (Encompassing Control Cost) when con-  
727 trol components are deployed symmetrically by policymakers and align  
728 with the shared confinement and vaccination types, as listed in Eq. (10).  
729 Currently, the complexity of our model’s ontology relies on simulated hy-  
730 pothetical data for analysis and heuristics. Real-world data should provide  
731 more accurate insights, but such data may not be available at the same level  
732 of detail and may not easily inform the model’s parametrization.

## 733 6. Conclusions

734 Our study addresses the critical intersection of supply chain manage-  
735 ment and public health policy during epidemic scenarios. We developed a  
736 comprehensive model that integrates an individual-based multiplex net-  
737 work ontology and a probabilistic SEIRSD-dynamic framework to evaluate  
738 the resilience and viability of supranational supply chains under various  
739 control strategies. Our model complements existing literature by incorpo-  
740 rating detailed cost components and leveraging Nash equilibrium analysis  
741 for performance metrics to identify optimal control strategies.

742 The problem of balancing supply chain performance with public health  
743 control measures has been a challenge, especially highlighted during the  
744 COVID-19 pandemic. Our model provides an encompassing approach to  
745 this problem by focusing on four primary cost components: deployed con-  
746 trol strategy, epidemic-related health policy deployment, value of human  
747 life, and epidemic-related loss of economic productivity, and by introducing  
748 resilience and viability metrics for supply chains. The costs are adjusted  
749 for GDP differences between countries and are influenced by factors such  
750 as the duration and severity of restrictions, vaccine efficacy, and healthcare  
751 capacity. While the supply chain metrics are specified for different location  
752 spreading between groups or regions.

753 By utilizing the SEIRD-probabilities of the nodes in the supply chain  
754 subset  $V_{SC}$ , we derived effective metrics for Time To Recovery (TTR) and  
755 Longitudinal Service Level (LSL). TTR is estimated based on the time it

756 takes for a significant proportion of nodes to reach a threshold recovery  
757 probability (after minimum performance), while LSL is assessed by har-  
758 monically averaging the activity probabilities over time (Susceptible and  
759 Recovered). These metrics provide a quantitative approach to understand-  
760 ing and managing supply chain resilience and performance.

761 Our numerical simulations revealed several key observations:

762 - Policymakers and supply chain managers often have conflicting opti-  
763 mal strategies, particularly when balancing Epidemic Control Costs (ECC)  
764 with TTR and LSL.

765 - The spread value of supply chains significantly influences the degree  
766 of conflict or convergence between policymakers and supply chain man-  
767 agers.

768 - Intermediate spread values introduce a more complex dynamic, often  
769 fostering synergetic deployments and balanced risk spreading in supply  
770 chain location.

771 In our approach, resilience and viability of supply chains are monitored  
772 using the robust metrics of TTR and LSL. While these metrics can be easily  
773 derived from epidemic state vectors of the individuals in the network, these  
774 should be further validated and, also derived in models for major disrupt-  
775 tions of non-epidemic nature, while various additional performance metrics  
776 could be envisaged. The present model framework could be expanded to  
777 integrate real-world data and network structures, enhancing its accuracy  
778 and including relevant agents in future developments. These improved  
779 models should be adapted dynamically as new data becomes available over  
780 time, reaching thresholds or providing measures to update effective policies.  
781 An expansion of the model to include other types of disruptions, such as  
782 major geopolitical events or global resource depletion, is envisaged to make  
783 it more versatile and applicable across different contexts. Previous develop-  
784 ments on the psychological effect of infectivity [Broekaert et al. \(2024a\)](#) and  
785 preference [Broekaert et al. \(2022\)](#) included human behavior in relation to  
786 disease and policies; however, behavioral economics could also demonstrate  
787 how individuals and organizations might respond to various control mea-  
788 sures beyond purely economic considerations. The generic structure of the  
789 supply chains left specifics of different industries with varying structures  
790 open, which could provide insights into industry-specific vulnerabilities  
791 when adopted, and improve the forecasting of supply chain performance.

792 In conclusion, our model offers an effective framework for policymakers  
793 and supply chain managers to make informed decisions during prolonged

794 epidemic conditions, ensuring the resilience and viability of supply chains.  
795 Continuous monitoring and dynamic policy adjustments based on our  
796 metrics can help mitigate the adverse effects of epidemics on supranational  
797 supply networks.

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## 985 Appendices

### 986 Appendix A. The social contact algorithm

987 The typical dense clustering of human social contacts is expressed by  
988 the clustering degree of each node  $k$  in the graph. Formally the cc is "It is  
989 obtained by dividing the number of edges between a vertex's neighbors  
990 by the number of edges that could possibly exist." or equivalently by the  
991 fraction of all existing triangles through node  $k$  and all possible triangles  
992 among  $k$ 's neighbors. Both distributions derived from the artificial networks  
993 –from the adjacency creation algorithm– need to show representative values  
of typical human contact networks (Barrett et al., 2009).

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#### Algorithm 1 Adjacency Creator Function

---

```
1: Function adjacency_creator( $N, D\_T, D\_W, D\_S, D\_eow, pMid, pEnd, weight$ )
2: Generate upper triangular indices for an  $N \times N$  matrix
3:  $row\_indices, col\_indices \leftarrow generate\_upper\_triangular\_indices(N)$ 
4: Calculate distances from main and secondary diagonals
5:  $D \leftarrow absolute\_difference(row\_indices, col\_indices)$  {Distance from main diagonal}
6:  $d \leftarrow absolute\_difference(row\_indices + col\_indices + 1, N)$  {Distance from secondary diagonal}
7: Calculate connection probabilities based on distances
8:  $a \leftarrow \exp\left(\frac{-(N-1-d)}{D\_eow}\right)$  {Probability towards "end of world"}
9:  $b \leftarrow \exp\left(\frac{-(N-2)}{D\_eow}\right)$  {Base probability}
10:  $pDiag \leftarrow pEnd \cdot \left(\frac{a-b}{1-b}\right) + pMid \cdot \left(\frac{1-a}{1-b}\right)$  {Combined probability}
11: Calculate ordered probabilities for different confinement types
12:  $pOrd\_X \leftarrow pDiag \cdot \exp\left(\frac{-(D-1)}{D\_X}\right), \forall X \in \{T, W, S\}$ 
13:  $D\_XY \leftarrow \frac{D\_X + D\_Y}{2}, \forall X, Y \in \{T, W, S\}$ 
14:  $pOrd\_X \leftarrow pDiag \cdot \exp\left(\frac{-(D-1)}{D\_X}\right), \forall X \in \{TW, WS, TS\}$ 
15: Shuffle the ordered probabilities to create unordered probabilities
16:  $pUnord\_X \leftarrow shuffle\_probabilities(pOrd\_X), \forall X \in \{T, W, S, TW, WS, TS\}$ 
17: Combine ordered and unordered probabilities using the weight
18:  $delimiter\_X \leftarrow pOrd\_X \cdot weight + (1 - weight) \cdot pUnord\_X, \forall X \in \{T, W, S, TW, WS, TS\}$ 
19: Generate candidate random values for probabilistic realization
20:  $candidate \leftarrow generate\_random\_values(delimiter\_T.shape)$ 
21: Create probabilistic realizations of adjacency matrices
22:  $proto\_X \leftarrow (candidate < delimiter\_X) \cdot 1, \forall X \in \{T, W, S, TW, WS, TS\}$ 
23: Initialize adjacency matrices
24:  $adj\_mat\_X \leftarrow proto\_X, \forall X \in \{T, W, S, TW, WS, TS\}$ 
25: return  $adj\_mat\_T, adj\_mat\_W, adj\_mat\_S, adj\_mat\_TW, adj\_mat\_TS, adj\_mat\_WS$ 
```

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994

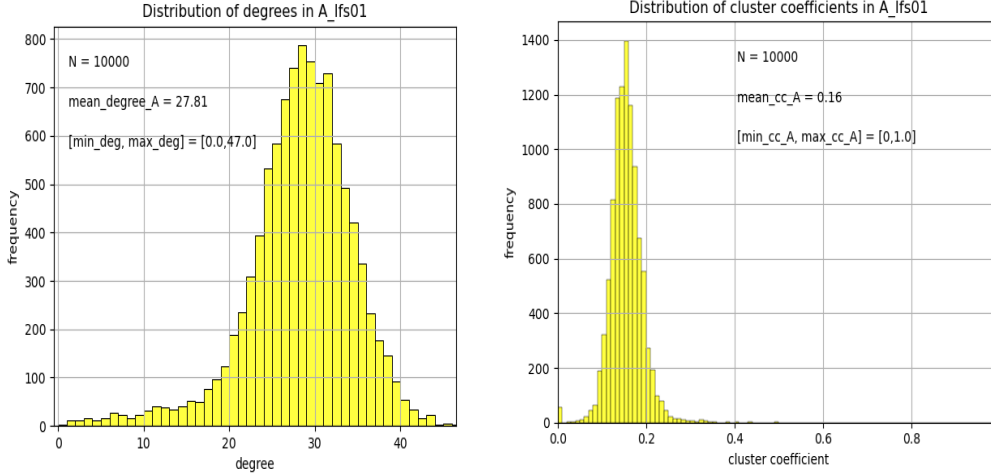


Figure A.4: The distribution of heterogenous social contact degree in the network under strict regional isolation  $A_{ifs01}$  (left) and the high clustering value of nodes (right).

995 **Appendix B. Epidemic network dynamics**

996 For each node, five probabilities define its state within one of the respec-  
 997 tive conditions  $\{S, E, I, R, D\}$ :  $\mathbf{\Pi}_k(t) = (p_{S,k}(t), p_{E,k}(t), p_{I,k}(t), p_{R,k}(t), p_{D,k}(t))$ .  
 998 These probabilities can be regrouped into graph-based  $N$ -dimensional seg-  
 999 ment vectors  $\mathbf{p}_X(t) = (p_{X,1}(t), \dots, p_{X,N}(t))$ , defined for each characteristic  
 1000  $X \in \{S, E, I, R, D\}$ . These probabilities evolve based on the disease's im-  
 1001 pact on each node's ego-network, which is variable for each individual  
 1002 and includes only those edges of the full graph  $E_{eg}$  where the individual is  
 1003 the central node connected to its first neighbors. The adjacency of nodes,  
 1004 represented by the matrix  $A$ , is thus a critical factor in the progression of an  
 1005 epidemic.

1006 The individual-based model extends the original approach by [Kermack](#)  
 1007 [and McKendrick \(1927\)](#), where the infectious force is proportional to the  
 1008 product of the susceptible (S) and infectious (I) components. Similar prod-  
 1009 uct terms have been included for social recovery effects [Wong and Kohler](#)  
 1010 [\(2020\)](#) and the impact of re-exposure on immunity loss ([Wu et al., 2021](#)),  
 1011 as well as for the observed waning of immunity ([Levin et al., 2021](#); [Saad-](#)  
 1012 [Roy et al., 2020](#)). The waning immunity effect introduces the possibility  
 1013 of a cyclic trajectory, as the Recovered component can decay back into the  
 1014 Susceptible component, hence the designation 'SEIRSD' network model.

1015 The epidemic system includes the following factors for each node in its  
 1016 governing equations:

1017 1. **(S → E): Exposure** arises from the infection term  $\mathbf{p}_S \circ A(\boldsymbol{\beta}_{\mathcal{G}} \circ \mathbf{p}_I)$ ,  
 1018 which combines a node's susceptibility with the infectiousness in its ego-  
 1019 network, scaled by  $\beta$ . This corresponds to each node's role as a susceptible  
 1020 'subject' and 'infector'.

1021 2. **(E → I and E → R): Disease outbreak** resulting in infection is caused  
 1022 by exposure to the virus,  $\boldsymbol{\lambda} \circ \mathbf{p}_E$ , and manifests later with latency  $\boldsymbol{\lambda}$ . The  
 1023 dominant channel-weight of  $1 - \varepsilon$  leads to the Infectious state, while a less  
 1024 common channel-weight  $\varepsilon$  leads to the Recovered state according to the first  
 1025 recovery rate,  $\boldsymbol{\delta}_1$ .

1026 3. **(I → R): Basic ('second') recovery** from the disease,  $\boldsymbol{\delta}_2 \circ \mathbf{p}_I$ , is further  
 1027 enhanced by social support from the ego-network's Recovered component,  
 1028  $\boldsymbol{\delta}_2 \circ \mathbf{p}_I A \boldsymbol{\sigma}_{\mathcal{G}} \circ \mathbf{p}_R$ .

1029 4. **(I → D): Virulence** term  $\boldsymbol{\nu} \circ \mathbf{p}_I$  is mitigated by social support strength  
 1030 from the ego-network,  $\boldsymbol{\nu} \circ \mathbf{p}_I \circ A(\boldsymbol{\sigma}_{\mathcal{G}} \circ \mathbf{p}_R)$ .

1031 5. **(R → S): Waning immunity** term,  $\boldsymbol{\rho} \circ \mathbf{p}_R$ , is diminished by re-exposure  
 1032 to the disease in the node's ego-network,  $\boldsymbol{\rho} \circ \mathbf{p}_R \circ A(\boldsymbol{\gamma}_{\mathcal{G}} \circ \mathbf{p}_I)$ .

1033 These factors lead to the  $5 \times N$  coupled governing equations of the  
 1034 graph-based epidemic system:

$$\begin{bmatrix} \dot{\mathbf{p}}_S \\ \dot{\mathbf{p}}_E \\ \dot{\mathbf{p}}_I \\ \dot{\mathbf{p}}_R \\ \dot{\mathbf{p}}_D \end{bmatrix} = \begin{bmatrix} -\mathbf{p}_S \circ A(\boldsymbol{\beta}_{\mathcal{G}} \circ \mathbf{p}_I) + \boldsymbol{\rho} \circ \mathbf{p}_R \circ (1 - A(\boldsymbol{\gamma}_{\mathcal{G}} \circ \mathbf{p}_I)) \\ \mathbf{p}_S \circ A(\boldsymbol{\beta}_{\mathcal{G}} \circ \mathbf{p}_I) - (1 - \varepsilon)\boldsymbol{\lambda} \circ \mathbf{p}_E - \varepsilon\boldsymbol{\delta}_1 \circ \mathbf{p}_E \\ (1 - \varepsilon)\boldsymbol{\lambda} \circ \mathbf{p}_E - \boldsymbol{\delta}_2 \circ \mathbf{p}_I \circ (1 + A(\boldsymbol{\sigma}_{\mathcal{G}} \circ \mathbf{p}_R)) - \boldsymbol{\nu} \circ \mathbf{p}_I \circ (1 - A(\boldsymbol{\sigma}_{\mathcal{G}} \circ \mathbf{p}_R)) \\ \varepsilon\boldsymbol{\delta}_1 \circ \mathbf{p}_E + \boldsymbol{\delta}_2 \circ \mathbf{p}_I \circ (1 + A(\boldsymbol{\sigma}_{\mathcal{G}} \circ \mathbf{p}_R)) - \boldsymbol{\rho} \circ \mathbf{p}_R + \boldsymbol{\rho} \circ \mathbf{p}_R \circ A(\boldsymbol{\gamma}_{\mathcal{G}} \circ \mathbf{p}_I) \\ \boldsymbol{\nu} \circ \mathbf{p}_I \circ (1 - A(\boldsymbol{\sigma}_{\mathcal{G}} \circ \mathbf{p}_R)) \end{bmatrix} \quad (\text{B.1})$$

1035 It is easily verified that this system conserves the total state probability  
 1036 for each node, as all terms on the right-hand side cancel on summation;  
 1037  $|\boldsymbol{\Pi}_k(t)|_1 = 1, \forall k \in [1 \cdots N], \forall t \in \mathbb{R}^+$ .

1038 **Appendix C. Epidemic Control Cost**

1039 Our model primarily emphasizes four cost components related to the  
1040 epidemic:

- 1041 • **Deployed Control Strategy:** These costs include the development and  
1042 production of vaccination technology, its deployment, and the imple-  
1043 mentation costs of confinement policies. Implementing a confinement  
1044 strategy incurs various costs for policymakers, such as enforcement,  
1045 logistics, possible compensations, support measures, reorganization  
1046 of education, and additional social services. A heuristic expression  
1047 for the cost of confinement considers i) the relative duration of the  
1048 restriction, ii) the relative severity of contact reduction, and iii) a pre-  
1049 sumed lower operation cost in lower-GDP countries.

1050 Similarly, the relative cost of vaccination is evaluated based on i) Vac-  
1051 cine efficacy ( $e$ ), ii) the relative duration of development and deploy-  
1052 ment, and iii) the presumed higher investment costs in lower-GDP  
1053 countries.

- 1054 • **Epidemic-Related Health Policy Deployment:** Initially, health costs  
1055 are proportional to the Infection-load value, serving as a proxy for  
1056 the number of treated or hospitalized patients. An investment cost  
1057 is triggered when the projected Infection-load challenges the limited  
1058 maximal capacity of the health infrastructure (e.g., ICU beds). When  
1059 the augmented healthcare structure is employed, further day-to-day  
1060 deployment in that configuration incurs higher proportional costs.  
1061 These transitions are implemented through a thresholded piecewise-  
1062 linear expression,  $\mathcal{I}(I, I_{max})$ , with an initial convex dependency on  
1063 the expected I-load (under a control strategy) and the uncontrolled  
1064 I-load,  $I_{max} = I_{No-No}$ , when the epidemic ranges freely:

$$\mathcal{I}(I, I_{max}) = \begin{cases} I & : I < I_{max}d_t^{-1} \\ I_{max}d_t^{-1}(1-f_e) + f_eI & : I_{max}d_t^{-1} < I < I_{max}d_c^{-1} \\ I_{max}(d_t^{-1}(1-f_e) + d_c^{-1}(f_e-f_p)) + f_pI & : I > I_{max}d_c^{-1} \end{cases} \quad (C.1)$$

1065 The fraction of the projected  $I_{max}$ -load to trigger augmented facilities  
1066 is fixed at  $d_t = 4$  ('trigger fraction'), and the cost increases by a factor,  
1067  $f_e = 3$  ('expansion'). This includes refurbishing and stocking medical  
1068 facilities, occurring well before existing capacity is reached, set at

1069 fraction  $d_c = 3$  ('capacity fraction') of the projected  $I_{max}$ -load. A  
 1070 cost increase for day-to-day deployment by a factor,  $f_p = 1.25$  ('post-  
 1071 operation'), is assumed for yet unreached efficient operation levels.

- 1072 • Value of Human Life (Death Toll): The private and public costs of  
 1073 deceased individuals are proportional to the death count value.
- 1074 • Epidemic-Related Loss of Economic Productivity: Assuming constant  
 1075 capital during the epidemic, a Cobb-Douglas production function  
 1076 for economic output is proportional to  $L^b$ . The optimal activation in  
 1077 the healthy network is set to the theoretical labor share  $L_{max} = 0.9$ .  
 1078 Due to the epidemic, the effective activation level in the population  
 1079 diminishes. The probabilistic system state vectors  $R$  and  $S$  provide  
 1080 the fraction of the network population remaining in a production role.  
 1081 The loss of productivity is proportional to the drop-out ( $E + I + D$ )  
 1082 relative to full production capacity.

1083 The defined load-expressions, Eq.(11), longitudinally capture the maximal  
 1084 probabilities to realize the SEIRD characteristics for each node, providing a  
 1085 variable to adequately parametrize various cost instances over the epidemic.  
 1086 Instead of targeting the minimum of the time-integrated cost, the optimal  
 1087 strategy results from the Nash equilibrium analysis of the game matrix of  
 1088 SEIRD load-based costs for all crossed strategies. The SEIRD load-based  
 1089 total incurred epidemic cost for each subpopulation  $\alpha$  on the graph of two  
 1090 countries,  $\alpha \in \{0, 1\}$ , is given by:

$$ECC_\alpha = c_{cs,\alpha} + c_{I,\alpha} \mathcal{J}(I_\alpha, I_{max\alpha}) + c_{D,\alpha} D_\alpha + c_{L,\alpha} L_{max}^b \left(1 - (1 - E_\alpha - I_\alpha - D_\alpha)\right) \quad (12)$$

1091 This equation includes the cost of disease-related health policy  $c_{I,\alpha}$ , the  
 1092 implementation cost of the control strategy  $c_{cs,\alpha}$ , the cost of deceased in-  
 1093 dividuals  $c_{D,\alpha}$ , and the impact on epidemic-related loss of economic labor  
 1094 force  $c_{L,\alpha}$ . Following Gros et al. (2021), the proportionality factors of cost  
 1095 can be expressed in relation to annual GDP per capita (for OECD countries),  
 1096 allocating a cost of 0.140 on the infected fraction when the value of life cost is  
 1097 omitted. In the SEIRSD model, this cost is re-scaled to the death component  
 1098 by applying the ratio of the mean transition periods ( $I$  to  $R$  flow and  $I$  to  $D$   
 1099 flow), i.e.,  $\delta_2/\nu$ .

1100 The population-specific implementation cost of their control strategy,  
 1101  $c_{cs,\alpha} \in \mathbb{R}$ ,  $\alpha \in \{0, 1\}$  and  $cs \in CS$ , is separated along confinement, vaccina-  
 1102 tion and isolation type and summed when strategies are combined:

$$c_{cs,\alpha} \in [0, c_{C_{ss}}, c_{C_{wl}}, c_{V_{el}}, c_{V_{lh}}, c_{C_{ss}} + c_{V_{el}}, c_{C_{ss}} + c_{V_{lh}}, c_{C_{wl}} + c_{V_{el}}, c_{C_{wl}} + c_{V_{lh}}]_{\alpha} \quad (C.3)$$

1103 incremented with  $c_{I_{fs01}}$  or  $c_{I_{pl01}}$  for effective isolation strategies. The direct  
 1104 summation of cost summands assumes no interference nor synergy with  
 1105 respect to the total cost of hybrid strategies. The simulation is implemented  
 1106 for two subpopulations with a GDP difference factor  $(1 - GDP_{diff})$ , with  
 1107  $GDP_{diff} = .1$ . Subpopulation 1 is the reference, and subpopulation group-0  
 1108 is corrected for its limited resources by a factor  $(1 - GDP_{diff})$ .

1109 The cost of intervention from the implemented control strategy,  $c_{cs,\alpha}$ ,  
 1110 is scaled in relation to health policy deployment, cost of life, and loss of  
 1111 productivity by a factor  $CS_{scale}$ . To assess the impact of the relative size of this  
 1112 intervention cost on the choice of the optimal control strategy, a variable  
 1113 range of  $CS_{scale}$  has been tested,  $CS_{scale} = 1.5$ .<sup>8</sup> The relative cost  $CV_{ratio}$   
 1114 of deploying a confinement strategy versus a vaccination strategy is also  
 1115 variable. We estimate the relative deployment cost of confinement, based on  
 1116 the analysis of [Gollier \(2021\)](#) on the cost of vaccination, to range in smaller  
 1117 fractions of the latter;  $CV_{ratio} = .1$ , resulting in respective cost scale factors  
 1118 for confinement,  $C_{scale} = CV_{ratio} CS_{scale}$ , and vaccination,  $V_{scale} = CS_{scale}$ . The  
 1119 cost correlation factors are implemented as follows:

$$c_I = c_L = 0.140 \cdot [1 - GDP_{diff}, 1], \quad c_D = 0.155 \delta_2 / \nu \cdot [1 - GDP_{diff}, 1], \quad (C.4)$$

1120 where the GDP-differentiated correlation factors  $c_{I,\alpha}$ ,  $c_{D,\alpha}$ , and  $c_{L,\alpha}$  for  
 1121 the two populations  $\alpha$  are juxtaposed in the list; e.g.,  $c_I = [c_{I,0}, c_{I,1}]$ . The  
 1122 parameters of the confinement strategy impact its operation cost. The rel-  
 1123 ative confinement duration and the relative severity of contact reduction  
 1124 are implemented as proportional factors, with a lower operation cost in the  
 1125 country with the relatively lower GDP. Formally, the confinement severity  
 1126 is expressed as a relative deviation from the average number of contacts

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<sup>8</sup>In ([Broekaert et al., 2024c](#)) a more extensive range  $CS_{scale} \in \{.4, 1, 1.5, 2, 3, 4, 5\}$  and  $CV_{ratio} \in \{.1, .2\}$  and  $GDP_{diff} \in \{.05, .1, .15, .20\}$  is reported and tested.

1127 under normal circumstances without an epidemic:

$$c_{C_{SS}} = \text{scaleC} \cdot \left( \frac{D_T - D_S}{D_T} \right) \cdot \frac{\text{dur}_{C_{SS}}}{\text{dur}_{C_{Wl}}} [(1 - \text{GDP}_{\text{diff}}), 1], \quad (\text{C.5})$$

1128

$$c_{C_{Wl}} = \text{scaleC} \cdot \frac{D_T - D_W}{D_T} \cdot \frac{\text{dur}_{C_{Wl}}}{\text{dur}_{C_{Wl}}} [(1 - \text{GDP}_{\text{diff}}), 1]. \quad (\text{C.6})$$

1129 While for isolation types the cost is estimated similarly

$$c_{I_{fs01}} = \frac{\text{dur}_{I_{fs}}}{\text{dur}_{I_{pl}}} [(1 - \text{GDP}_{\text{diff}}), 1], \quad (\text{C.7})$$

1130

$$c_{I_{pl01}} = \frac{\text{dur}_{I_{pl}}}{\text{dur}_{I_{pl}}} \cdot (\text{frac\_isol}^2) [(1 - \text{GDP}_{\text{diff}}), 1], \quad (\text{C.8})$$

1131 where a non-linear dependence is assumed in the severity of closing of the  
1132 frontiers.

1133 The operation and development cost of the vaccination strategy is ex-  
1134 pressed by the factors of i) vaccine efficacy ( $e$ ), reflecting advanced phar-  
1135 maceutical technology, ii) relative duration of the industrial development  
1136 and deployment process and, iii) presumed higher required investment  
1137 costs in the lower-GDP country.

$$c_{V_{el}} = V_{\text{scale}} e_{V_{el}} \left( \frac{t_{\text{start}_{V_{el}}}}{t_{\text{start}_{V_{lh}}}} \right) \cdot [1 + \text{GDP}_{\text{diff}}, 1], \quad (\text{C.9})$$

$$c_{V_{lh}} = V_{\text{scale}} e_{V_{lh}} \left( \frac{t_{\text{start}_{V_{lh}}}}{t_{\text{start}_{V_{lh}}}} \right) \cdot [1 + \text{GDP}_{\text{diff}}, 1], \quad (\text{C.10})$$

1138 **Appendix D. Game matrices for ECC**

1139 The multiple ECC-based Nash strategy profiles for the isolation types  $Igo_{01}$ ,  $Ifs_{01}$ , and  $Ipl_{01}$  need to be compared and one selected.

$Igo_{01}$	$No_1$	$Css_1$	$Cwl_1$	$Vel_1$	$Vlh_1$	$CssVel_1$	$CssVlh_1$	$CwlVel_1$	$CwlVlh_1$
$No_0$	0.227 / 0.252	0.249 / 0.248	0.226 / 0.236	0.226 / 0.214	0.227 / 0.376	0.225 / 0.205	0.226 / 0.357	0.225 / 0.213	0.226 / 0.368
$Css_0$	0.252 / 0.250	0.252 / 0.246	0.252 / 0.234	0.251 / 0.212	0.252 / 0.375	0.251 / 0.204	0.252 / 0.356	0.251 / 0.211	0.252 / 0.366
$Cwl_0$	0.257 / 0.250	0.256 / 0.246	0.257 / 0.234	0.256 / 0.213	0.257 / 0.375	0.256 / 0.204	0.256 / 0.356	0.256 / 0.212	0.257 / 0.366
$Vel_0$	0.241 / 0.250	0.240 / 0.245	0.240 / 0.233	0.239 / 0.211	0.240 / 0.373	0.239 / 0.203	0.240 / 0.354	0.239 / 0.210	0.240 / 0.365
$Vlh_0$	0.389 / 0.251	0.388 / 0.247	0.388 / 0.236	0.388 / 0.213	0.388 / 0.376	0.387 / 0.205	0.388 / 0.357	0.387 / 0.213	0.388 / 0.368
$CssVel_0$	0.246 / 0.248	0.245 / 0.243	0.245 / 0.231	0.245 / 0.210	0.245 / 0.372	0.244 / 0.202	0.245 / 0.327	0.244 / 0.210	0.245 / 0.364
$CssVlh_0$	0.392 / 0.250	0.391 / 0.246	0.392 / 0.234	0.391 / 0.212	0.392 / 0.374	0.391 / 0.204	0.391 / 0.330	0.391 / 0.211	0.391 / 0.366
$CwlVel_0$	0.227 / 0.249	0.249 / 0.244	0.226 / 0.232	0.225 / 0.211	0.226 / 0.373	0.225 / 0.202	0.226 / 0.327	0.225 / 0.210	0.226 / 0.364
$CwlVlh_0$	0.397 / 0.250	0.396 / 0.246	0.396 / 0.234	0.396 / 0.212	0.397 / 0.375	0.395 / 0.204	0.396 / 0.330	0.395 / 0.212	0.396 / 0.366
$Ifs_{01}$	$No_1$	$Css_1$	$Cwl_1$	$Vel_1$	$Vlh_1$	$CssVel_1$	$CssVlh_1$	$CwlVel_1$	$CwlVlh_1$
$No_0$	0.286 / 0.314	0.309 / 0.305	0.286 / 0.292	0.286 / 0.273	0.286 / 0.435	0.309 / 0.265	0.286 / 0.387	0.286 / 0.246	0.286 / 0.424
$Css_0$	0.311 / 0.340	0.312 / 0.305	0.311 / 0.292	0.311 / 0.273	0.311 / 0.435	0.312 / 0.266	0.311 / 0.387	0.311 / 0.272	0.311 / 0.424
$Cwl_0$	0.316 / 0.314	0.316 / 0.305	0.292 / 0.292	0.316 / 0.273	0.292 / 0.435	0.316 / 0.265	0.292 / 0.387	0.292 / 0.246	0.292 / 0.398
$Vel_0$	0.300 / 0.314	0.300 / 0.304	0.300 / 0.291	0.300 / 0.273	0.300 / 0.435	0.300 / 0.265	0.300 / 0.387	0.300 / 0.246	0.300 / 0.423
$Vlh_0$	0.447 / 0.314	0.447 / 0.305	0.447 / 0.292	0.447 / 0.273	0.447 / 0.435	0.447 / 0.265	0.447 / 0.387	0.447 / 0.246	0.447 / 0.398
$CssVel_0$	0.305 / 0.314	0.306 / 0.305	0.305 / 0.292	0.305 / 0.273	0.282 / 0.435	0.305 / 0.265	0.282 / 0.387	0.282 / 0.246	0.282 / 0.423
$CssVlh_0$	0.451 / 0.314	0.451 / 0.305	0.451 / 0.292	0.451 / 0.273	0.451 / 0.435	0.451 / 0.265	0.451 / 0.387	0.451 / 0.246	0.451 / 0.398
$CwlVel_0$	0.286 / 0.314	0.309 / 0.304	0.286 / 0.291	0.286 / 0.273	0.286 / 0.435	0.286 / 0.265	0.286 / 0.387	0.286 / 0.246	0.286 / 0.397
$CwlVlh_0$	0.455 / 0.314	0.455 / 0.304	0.455 / 0.292	0.455 / 0.273	0.455 / 0.435	0.455 / 0.265	0.455 / 0.387	0.455 / 0.246	0.455 / 0.398
$Ipl_{01}$	$No_1$	$Css_1$	$Cwl_1$	$Vel_1$	$Vlh_1$	$CssVel_1$	$CssVlh_1$	$CwlVel_1$	$CwlVlh_1$
$No_0$	0.288 / 0.320	0.311 / 0.316	0.288 / 0.305	0.287 / 0.282	0.288 / 0.445	0.287 / 0.273	0.288 / 0.426	0.287 / 0.282	0.288 / 0.437
$Css_0$	0.314 / 0.319	0.313 / 0.314	0.313 / 0.302	0.313 / 0.281	0.314 / 0.443	0.312 / 0.273	0.313 / 0.424	0.312 / 0.280	0.313 / 0.435
$Cwl_0$	0.319 / 0.319	0.318 / 0.315	0.318 / 0.303	0.318 / 0.281	0.319 / 0.444	0.317 / 0.273	0.318 / 0.424	0.318 / 0.281	0.318 / 0.435
$Vel_0$	0.302 / 0.318	0.302 / 0.313	0.302 / 0.301	0.301 / 0.280	0.302 / 0.442	0.301 / 0.271	0.302 / 0.422	0.301 / 0.279	0.302 / 0.433
$Vlh_0$	0.450 / 0.320	0.449 / 0.316	0.450 / 0.304	0.449 / 0.282	0.450 / 0.444	0.449 / 0.273	0.449 / 0.425	0.449 / 0.281	0.450 / 0.436
$CssVel_0$	0.307 / 0.317	0.307 / 0.312	0.307 / 0.300	0.306 / 0.279	0.307 / 0.441	0.306 / 0.271	0.307 / 0.396	0.306 / 0.278	0.307 / 0.432
$CssVlh_0$	0.454 / 0.318	0.453 / 0.314	0.453 / 0.302	0.453 / 0.281	0.454 / 0.443	0.452 / 0.272	0.453 / 0.398	0.452 / 0.280	0.453 / 0.434
$CwlVel_0$	0.288 / 0.317	0.311 / 0.312	0.288 / 0.300	0.287 / 0.279	0.288 / 0.441	0.287 / 0.271	0.287 / 0.396	0.287 / 0.278	0.288 / 0.432
$CwlVlh_0$	0.459 / 0.319	0.458 / 0.315	0.458 / 0.302	0.457 / 0.281	0.459 / 0.443	0.457 / 0.273	0.458 / 0.398	0.457 / 0.280	0.458 / 0.435

Table D.5: The ECC pay-off matrices for the first Wave, Isolation type:  $Igo_{01}$  (top),  $Ifs_{01}$  (middle),  $Ipl_{01}$  (bottom), and  $GDP_{diff} = 0.15$ ;  $CS_{scale} = 1.5$  and  $CV_{ratio} = .1$  with selected Nash equilibrium for the  $Cwl_0\_Vel_0\_Css_1\_Vel_1$  control configuration, as appears in Table 3.