Epidemics 53 (2025) 100873

Contents lists available at ScienceDirect

Epidemics

journal homepage: www.elsevier.com/locate/epidemics

Integrating macroeconomic and public health impacts in social planning policies for pandemic response

Ofer Cornfeld [a], Kaicheng Niu [b], Oded Neeman [c], Michael Roswell [d], Gabi Steinbach [d], Stephen J. Beckett [d,e], Yorai Wardi [b,*], Joshua S. Weitz [d,e,f,*], Eran Yashiv [c,g,h,i,*]

[a] BFI, Tel Aviv, Israel
[b] School of Electrical and Computer Engineering, Georgia Institute of Technology, Atlanta, GA, United States of America
[c] The Eitan Berglas School of Economics, Tel Aviv University, Tel Aviv, Israel
[d] Department of Biology, University of Maryland, College Park, MD, United States of America
[e] University of Maryland Institute for Health Computing, North Bethesda, MD, United States of America
[f] Department of Physics, University of Maryland, College Park, MD, United States of America
[g] Center for Macroeconomics, London School of Economics, London, United Kingdom
[h] Centre for Research and Analysis of Migration, University of College London, London, United Kingdom
[i] IZA - Institute of Labor Economics, Bonn, Germany

ARTICLE INFO

Dataset link: https://github.com/odedneeman/Optimal-Pandemic-Control

Keywords:
Macroeconomics of epidemics
GDP loss
Health outcomes
Optimal and feedback control
Pandemic response

ABSTRACT

Infectious disease outbreaks with pandemic potential present challenges for mitigation and control. Policy-makers must reduce disease-associated morbidity and mortality while also minimizing socioeconomic costs of interventions. At present, robust decision frameworks that integrate epidemic and macroeconomic dynamics to inform policy choices, given uncertainty in the current and future state of the outbreak and economic activity, are not widely available. In this study, we propose and analyze an economic-epidemic model to identify robust planning policies that limit epidemic impacts while maintaining economic activity. We compare alternative fixed, dynamic open-loop optimal control, and feedback control policies via a welfare loss framework. We find that open-loop policies that adjust employment dynamically while maintaining a flat epidemic curve outperform fixed employment reduction policies. However, open-loop policies are highly sensitive to misestimation of parameters associated with intrinsic disease strength and feedback between economic activity and transmission, leading to potentially significant increases in welfare loss. In contrast, feedback control policies guided by open-loop dynamical targets of the time-varying reproduction number perform near-optimally when parameters are well-estimated, while significantly outperforming open-loop policies whenever disease transmission and population-scale behavioral response parameters are misestimated — as they inevitably are. Our study provides a template for integrating principled economic models with epidemic scenarios to identify policy vulnerabilities and expand policy options in preparation for future pandemics. Across disease scenarios, we show that policies that temporarily limit economic activity and disease transmission reduce both disease-driven mortality and cumulative loss of economic activity. Our study suggests that future preparedness depends on feasible, robust, and adaptive policies and can help avoid false dichotomies in choosing between public health and economic outcomes.

1. Introduction

Emerging and re-emerging infectious diseases threaten global health and socioeconomic well-being (Christakis, 2020; Ferguson et al., 2020). In response to the potential catastrophic threat of COVID-19, governments rapidly imposed social distancing and/or lockdowns to reduce contacts between susceptible and infectious individuals (including those who may be unaware they are infected Gandhi et al., 2020) as a means to reduce rates of new infections (Hellewell et al., 2020; Atkeson, 2021; Atkeson et al., 2021). Model-inferred estimates suggest that ∼ 3.1 million deaths were averted in 11 European countries between February–May 2020 due to national lockdowns (Flaxman et al., 2020), while social distancing policies in China, South Korea, Italy, Iran, France, and the United States led to more than 61 million averted cases between February–April 2020 (Hsiang et al., 2020). However, such counterfactuals come with significant caveats. First, baseline epidemic

* Corresponding authors.
E-mail addresses: ywardi@ece.gatech.edu (Y. Wardi), jsweitz@umd.edu (J.S. Weitz), yashiv@tauex.tau.ac.il (E. Yashiv).

https://doi.org/10.1016/j.epidem.2025.100873
Received 23 June 2025; Received in revised form 11 November 2025; Accepted 26 November 2025
Available online 28 November 2025

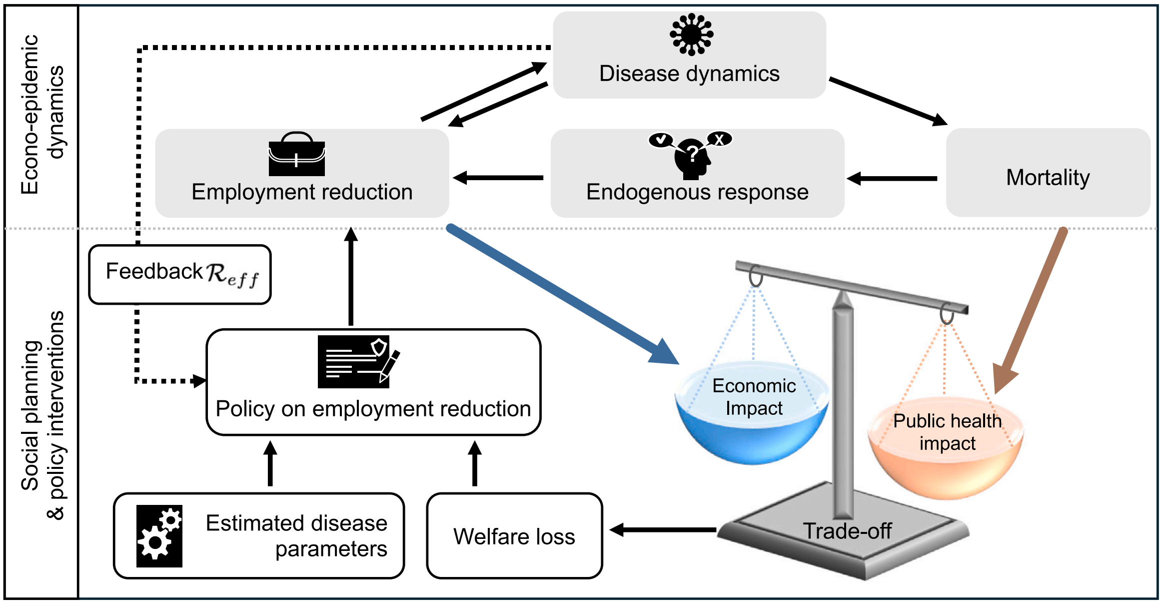

Fig. 1. Schematic of the econo-epidemic modeling framework with epidemic dynamics, macroeconomic model of welfare loss, endogenous response, and feedback with a social planning problem. The top section provides an overview of the underlying econo-epidemic model. The bottom section provides an overview of the social planning process that integrates economic and public health impact as a means to develop optimal policies (both open- and closed-loop) to minimize welfare loss through modification of employment reduction policies. Full specification of the epidemic model dynamics, economic model structure, control theoretic approach, policy planner optimization, and disease parameters are found in Supplementary Text A.

models do not typically integrate behavioral change (and/or alternative mitigation steps) that could lead to reduction in transmission and fatalities (Weitz et al., 2020). Second, even if early transmission is averted, subsequent relaxation of policies can lead to rapid resurgence of infections and fatalities (Du et al., 2023). Third, societal-scale lockdowns impose health costs, decreasing the frequency of regular clinical care visits including screening for cancers (McBain et al., 2021), while increasing social isolation that impacts the mental health of children and adults (Moreno et al., 2020).

Local, regional, and national lockdowns also come with substantive socioeconomic costs that are the subject of ongoing debate (Macedo and Lee, 2025). In macroeconomic terms, lockdowns reduce economic activity due to production declines and decreases in productivity, losses of revenue, and business closures that ripple across different economic sectors. People and policymakers are still dealing with the aftermath of lockdowns. For example, lockdowns are hypothesized to have fueled a burst of inflation (Jordà et al., 2022) driven, in part, by supply-chain disruptions. Likewise, changes in the labor market induced by the pandemic, including increases in remote work, shifts in jobs, industries, and employment patterns, and shifts in market demand have continued to impact economic productivity and gross domestic product worldwide (Amiti et al., 2024; Harding et al., 2023; Autor et al., 2023). In a 2024 public forum (Williams and Reis, 2024), the Federal Reserve Bank of New York President John Williams expressed dissatisfaction with econo-epidemic models. Inadequately integrating principled economic models with epidemic scenarios generates vulnerabilities in policy responses that prioritize one of health or economic outcomes at the expense of the other. As a result, there are unresolved questions on the links between epidemic dynamics, policy response, and economic impacts spanning increases in inflation, supply chain dilemmas, and changes in the labor market (Jordà et al., 2022; Amiti et al., 2024; Harding et al., 2023; Autor et al., 2023).

This paper addresses the gap between public health policies that aim to decrease the morbidity and mortality associated with disease outbreaks, and social planning policies that aim to stimulate and sustain economic activity. In doing so, we integrate both sets of goals in a common valuation framework and ask: what feasible policies minimize health impacts while maximizing economic activity? To address this question, we develop a social planning policy analysis framework that (i) includes realistic, feasible policy plans that account for lags in implementation and discrete policy periods; (ii) utilizes a common 'value of reduced mortality risk' (VRMR) framework for jointly evaluating the macroeconomic and public health effects of policy objectives — VRMR quantifies the equivalent substitution between averted deaths and money (Simon et al., 2019); (iii) accounts for behavioral response and the lack of precise information on (re)emerging diseases. We use this framework to evaluate three classes of policy types: (i) fixed control policies (that predefine interventions and do not change in time); (ii) dynamic open-loop optimal control policies (that are dynamic in time but predetermined at the outset); and (iii) feedback control policies (that are dynamic in time and are adjusted during the outbreak based on real-time measurements). By integrating a common valuation framework and evaluating policies through commonly measured indicators of disease impact, we explore when and how policy planners can feasibly achieve *nearly* optimal population-scale epidemic and economic objectives in the face of persistent uncertainty regarding transmission and responses at individual scales.

2. Results

2.1. Econo-epidemic modeling framework

We developed an integrated econo-epidemic modeling framework amenable to a social planning problem that can be used to identify 'optimal' policies given variation in disease transmission, behavioral response, and economic output (Fig. 1). To do so, we utilize a Susceptible–Exposed–Infectious–Recovered/Removed (SEIR) epidemic modeling framework to represent disease spread at population scales (full equations in Supplementary Information (SI) Text A). The time varying incidence, $\beta_t SI$, given the susceptible fraction S and infectious fraction I is modulated by the transmission rate

$$\beta_t = \beta_W - \beta_N \left(1 - \frac{n_t}{n_{SS}}\right)^{\alpha} + \beta_{\Lambda} \exp(-\Lambda t) \tag{1}$$

which is driven by a combination of factors: (i) baseline interactions when the economy is open ($\beta_W + \beta_{\Lambda}$); (ii) rapid behavioral adaptation of

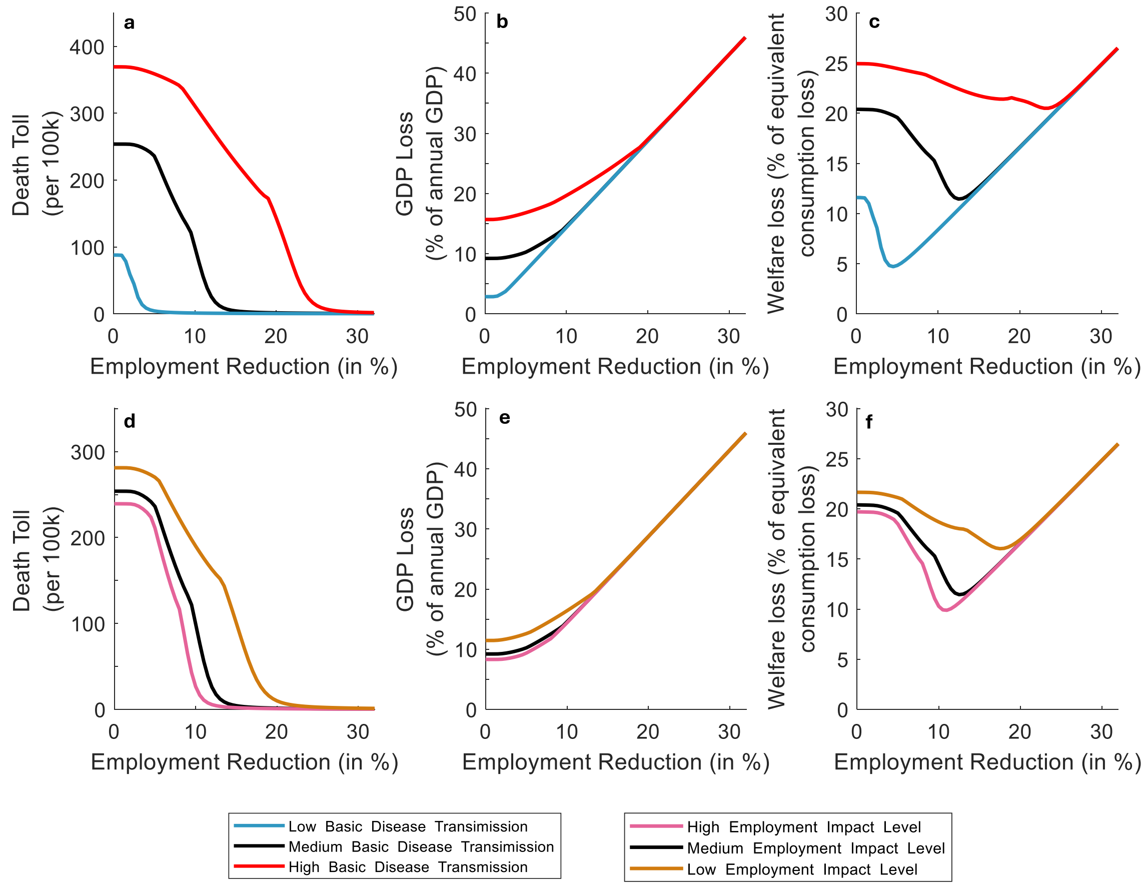

Fig. 2. Optimal fixed employment reduction policies reduce welfare loss, balancing impacts of cumulative fatalities and reduction in GDP. Panels (A)-(C) show the outcome of fixed employment reduction (on the x-axis) in terms of fatalities (per 100,000), GDP loss (%), and % welfare loss, respectively. The three curves in each panel denote outcomes given baseline (black, $\mathcal{R}_0 = 2.86$, $\beta_W = 0.376$), elevated (red, $\mathcal{R}_0 = 3.156$, $\beta_W = 0.45$), or reduced (blue, $\mathcal{R}_0 = 2.556$, $\beta_W = 0.3$) disease transmission conditions, consistent with variation in early estimates of COVID-19 strength (Park et al., 2020b). Likewise, Panels (D)-(F) show modulation of the impact of employment reduction on transmission using the disease parameters in the black curve conditions in Panels (A)-(C), given more impactful (pink, $\beta_N = 0.6$), and less impactful (orange, $\beta_N = 0.4$) conditions. The baseline employment impact is when $\beta_N = 0.53$. For each scenario in Panels (C) and (F) there is an optimal, fixed employment reduction policy which corresponds to the point at which welfare loss is at its minimum.

the population over a short time scale ($1/\Lambda$) uncoupled to employment levels that reduces transmission by β_Λ – this captures the initial learning phase after the outbreak onset; (iii) endogenous behavioral response arising from individual-level decisions not necessarily mandated by policy (e.g., working from home, masking, and improved ventilation in the case of respiratory diseases); (iv) policy-induced dynamic reduction in transmission. The realized employment level n_t relative to the steady-state economy n_{SS} leads to a reduction in transmission parameterized by β_N and an exponent α. The resulting time-dependent effective reproduction number is therefore $\mathcal{R}_t = S_t \frac{\beta_t}{\gamma}$, where γ is the removal rate of infectious individuals.

The disease model is coupled to a macroeconomic model in which the gross domestic product (GDP) is driven by a linear production function tied to employment, assuming constant wages and that output is fully consumed (see SI Text A). Employment is influenced by (i) individual-level economic activity guided by utility maximization linked to the severity of the disease outbreak, $b(\dot{D}_t, t)$, which we refer to as the endogenous behavioral response, and (ii) a social planner that imposes a level of preferred employment reduction, L_t. We assume that the realized employment reduction is the maximum of these two effects, i.e.,

$$n_t = 1 - (max\{b(\dot{D}_t, t), L_t\}). \tag{2}$$

In this combined econo-epidemic modeling framework, the objective of the central planner is to minimize welfare loss $WL\left(L_t\right)$ caused by the disease, balancing the death toll with the economic costs (i.e., cumulative work hours, see SI Text A). Welfare loss is a function of the policy L_t equivalent to the fractional employment reduction — which typically exceeds the endogenous response. Welfare loss is measured by economic utility/welfare units and is nonlinearly related to wages, level of economic utility, the death toll, and the disutility from working. Throughout, we consider the social planning problem over a time horizon T in which we expect the large-scale dissemination of effective vaccines (Supplementary Table S5).

2.2. Evaluation of fixed employment reduction policies to minimize welfare loss during a pandemic

In the absence of social planning interventions, an initially small fraction of infected individuals will catalyze an outbreak leading to transient reduction in employment due to utility maximization via the endogenous behavioral response. This scenario (Supplementary Figure S1) leads to large-scale outbreaks and significant loss of life. It also provides the baseline for evaluating alternative, fixed economic reduction policies intended to reduce welfare loss. To generate the baseline dynamics associated with basic reproduction number $\mathcal{R}_0$, we consider variation in fixed employment reduction policies across a continuum ranging from fully open to a maximally restricted economy (econo-epidemic model parameterization in Supplementary Table S5). Employment reduction reduces cumulative fatalities while increasing economic loss. We identify an optimal, intermediate lockdown level corresponding to a fixed policy that minimizes welfare loss compared to viable alternatives (see minima in welfare loss in the top panels of Fig. 2). Variation in either the intensity of baseline transmission (due to differences in disease features leading to changes in $\mathcal{R}_0$) or the efficacy of employment reduction on transmission lead to different optimal, fixed employment reduction policies (Fig. 2 bottom). Typically, increases in disease intensity and/or decreases in the efficacy of employment reduction on transmission increase the welfare loss associated with fixed, optimal policy responses. Hence, insofar as disease intensity and the link between employment reduction and transmission are known with certainty, there exists an optimal *fixed* response that can be planned in advance.

2.3. Open loop control policies outperform fixed lockdown policies in minimizing welfare loss during pandemics

We sought to identify and characterize optimal open loop, *time-dependent* policies given continuous variation in employment reduction levels n_t, rather than fixed employment reduction policies as explored in the previous section. To do so, we pose and solve an optimal control problem using a robust steepest-descent algorithm based on the maximum principle (detailed in the Supplementary Information). We utilize the employment reduction level, n_t, as the control variable accessible by the policy maker which influences transmission and the effective reproduction number. Fig. 3 panels (a-c) and (d-f) compare consequences for welfare loss and optimal control solutions $n_{oc}(t)$ for low, medium, and high basic transmission cases, spanning $\mathcal{R}_0 \approx 2.6$, 2.9, and 3.2 respectively. In each case, the optimal control algorithm identifies time-dependent changes in employment reduction (see Supplementary Figure S2 for disease dynamics, $\mathcal{R}_{eff}$, and welfare loss). Initially, the economy is restricted with significant economic cost. Given low prevalence (and low mortality), the rapid learning period reduces transmission (e.g., via masks, social distancing, and crowd avoidance), leading to a reduction of $\mathcal{R}_{eff}$ close to, but slightly above 1. Then, exponential increases in disease burden drives a second phase of reduced employment that exceeds employment reduction expected through the endogenous response alone. Hence, the open loop optimal control policy reduces $\mathcal{R}_{eff}$ slightly below 1. Finally, the expected arrival of an effective vaccine disseminated at high coverage allows the optimal planner a means to reduce restrictions. These three phases appear most evidently in the high disease scenario, but are present in each of the low, medium, and high transmission scenarios in the optimal continuous policy. The equivalent total welfare loss for the optimal *time-dependent* policy is shown as a function of $\mathcal{R}_0$ in panels (a)–(c). We also confirm that these time-dependent policies could be implemented feasibly, i.e., by restricting the interval length during which a policy could be changed. In practice, we offer the planner limited flexibility, showing that 3 policy regimes are sufficient for an 18-month intervention period. The optimal piecewise constant curves (i.e., 'optimal stepwise policies') are paired with each optimal continuous policy in panels (d)–(f), closely mimicking the optimal continuous policy both in shape and in performance. Notably, the optimal time-dependent policies (whether continuous or stepwise) each identify nearly the same level of employment reduction. However, the time at which the optimal control algorithm identifies the appropriate moment to shift between policies (initial, restricted, relaxed) varies with the underlying disease strength (see Supplementary Figure S2). This variation also suggests that misestimation of disease strength during the planning policy could lead to mismatched responses.

2.4. Fragility of optimal control policies given uncertainty

Optimal control problems can be sensitive to misspecification of parameters, especially when applied to nonlinear dynamic systems with the potential for (transient) exponential growth (Morris et al., 2021). Hence, we set out to evaluate the sensitivity of performance, as measured in terms of welfare loss, given solutions of the optimal control algorithm for parameters θ_{ref} when the disease outbreak is characterized by $\vec{\theta}_{alt} \neq \vec{\theta}_{ref}$. As above, the optimal control problem is solved using a model-based, open loop, offline computation yielding time-dependent policies for transmission that can be mapped to equivalent employment reduction policies n_t. Fig. 4 highlights the sensitivity of the optimal *time-dependent* policy to misspecification of parameters. The purple curves in panels (b)–(d) show the difference between the death toll, GDP loss, and welfare loss relative to the optimal time-dependent policy given a reference basic reproduction number (x-axis, vertical dashed line). When the pathogen is less transmissable, then the optimal policy will be overly cautious, leading to modest decreases in the death toll, substantial increases in GDP loss, and substantial increases in welfare loss, just as fixed policies are prone to misspecification errors (as in Fig. 2). Likewise, when the pathogen is more transmissable, then the optimal policy will be insufficiently cautious, leading to substantial increases in the death toll, modest improvements in GDP loss, and substantial increases in welfare loss (Fig. 2). Sensitivity analysis of misspecification of other parameters indicates that the optimal policy is fragile when the parameters directly affecting the reproduction number are misspecified (e.g., the impact of employment on the spread of the disease). In contrast, the policy remains robust to misspecification of parameters that influence the reproduction number only indirectly (e.g., the death rate, VRMR, or the expected arrival time of vaccine).

2.5. Robust feedback control in econo-epidemic models

Identifying optimal, time-dependent planning policies via open loop algorithms leads to improvements in welfare loss compared to fixed policies (see Fig. 3) provided they rely on accurate disease parameter estimates (see Fig. 4). However, a comparison of optimal time-dependent policies did yield a dynamical insight — despite differences in employment reduction associated with variations in underlying disease strength, the target levels of $\mathcal{R}_{eff}$ were relatively robust. For example, when varying $\mathcal{R}_0$ from 2.556 to 3.156, while we found approximately 400% relative differences in employment reduction during the restricted phase, the $\mathcal{R}_{eff}$ relative difference was around 6% (see Supplementary Figure S2). In this restricted phase, we observe an emergent feature of disease transmission dynamics — the disease is controlled at levels where $\mathcal{R}_{eff} < 1$, but only slightly so. Maintaining the effective reproduction number below 1 constrains exponential increases in incidence without paying the economic cost of more restrictive measures. Hence, we implemented a feedback control planning algorithm that tracks $\mathcal{R}_{eff}$ (note that real-time estimates of the effective reproduction number are increasingly accessible Gostic et al., 2020). We implement the feedback control using the proportional–integral–derivative (PID) control technique (Franklin et al., 2019) (the algorithm is detailed in Supplementary Text B.2). Fig. 4a specifies the resulting feedback control policy when optimized for the correct and mismatched disease parameters (both stronger and weaker than the reference parameters). Note that despite the misspecification, the feedback control policy identifies similar (albeit slightly lagged) shifts in the timing between initial, restricted, and relaxed phases. Moreover, the welfare loss under the feedback control policy is robust to misspecification of parameters. We show the robustness of outcomes with respect to the link between employment and transmission in Figure S4; similar results hold for variation in the death rate, the incubation period, the expected arrival time of vaccines, and the VRMR (value of reduced mortality risk). This robustness of policy response in the closed-loop case contrasts with the extreme sensitivity of the optimal time-dependent employment reduction policy identified through an open loop, optimal control algorithm (contrast green, feedback control with purple open loop, optimal control in Fig. 4d).

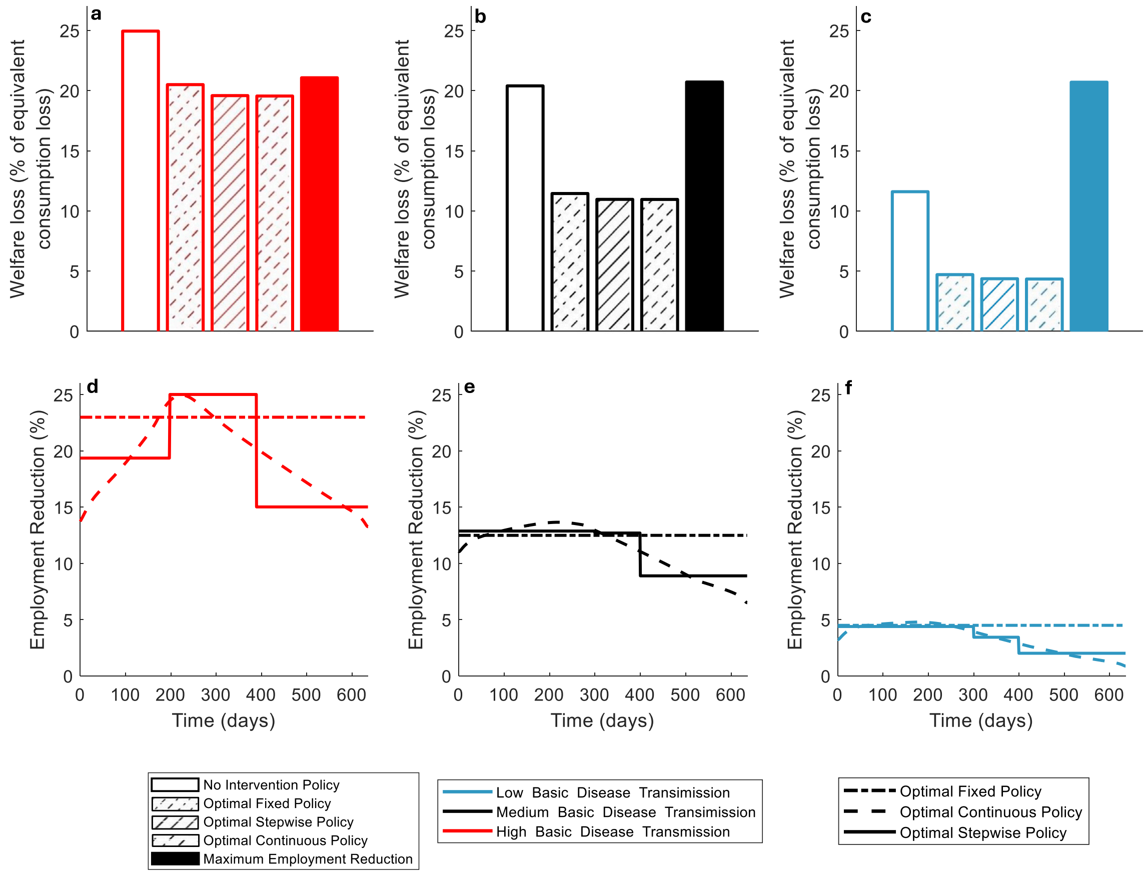

Fig. 3. Performance of open loop, optimal control policies across disease transmission conditions. Three optimal policies are contrasted with no intervention and maximal intervention options. The open loop policies include an optimal fixed, continuous, and stepwise policy. Panels (a)–(c) show the cumulative welfare loss for all five cases, in each case the optimal policies outperform either no intervention or full restrictions. Panels (d)–(f) show the employment reduction over time for the three optimal policies. Each of the three plots in the 2 panels denotes the policies and outcomes for 3 different disease transmission conditions: Low ($\mathcal{R}_0 = 2.56$), medium ($\mathcal{R}_0 = 2.86$), and high ($\mathcal{R}_0 = 3.16$). Across conditions, the optimal stepwise policy closely resembles the continuous optimal policy, and consistently outperform fixed policies.

3. Discussion

We developed and analyzed a social planning problem centered on an econo-epidemic model that couples transmission dynamics between individuals with changes in employment. Our objective was to identify a suite of feasible and robust social planning policies that could minimize welfare loss as measured in terms of the value of reduced mortality risk, i.e., accounting for fatalities averted during the pandemic as well as GDP decreases arising from employment reduction. In doing so, we considered a fully coupled model such that changes in disease severity would decrease employment through endogenous feedback which, in turn, would lead to decreases in transmission. The social planner then has the opportunity to go beyond endogenous response and restrict economic activity. As we show, although it is possible to devise an optimal, dynamic policy with reduced employment that outperforms any fixed policy (e.g., lockdowns or otherwise), such optimal dynamic policies can be extremely sensitive to misestimation of disease transmission parameters and/or the impact of economic activity on disease transmission. Indeed, implementing the incorrect 'optimal' dynamic policy can lead to mismatched timing of interventions and significant increases in welfare loss. Instead, we show that such optimal dynamic policies can be used as a guide for a feedback control policy, leveraging robustness properties and implementation principles of proportional–integral–derivative (PID) controllers. As a result, a social planner can implement a feedback control policy that is feasible (i.e., is implemented via a combination of fixed policy blocks), nearly-optimal (i.e., performs nearly as well as the optimal dynamic policy with perfect information), and robust to misspecification (i.e., continues to perform nearly as well as the optimal dynamic policy even when parameter estimations are misaligned with reality). If prepared in advance, such social planning policies could counter false dichotomies surrounding prioritization of public health or the economy.

The COVID-19 pandemic is unlikely to be the last. Increasing mobility that enables long-distance transmission, changes in climate that facilitate expansion of pathogen geographic ranges, and increasing stress placed at human-zoonotic interfaces can each contribute to increasing the pandemic potential of endemic and emerging pathogens. Specific threats include COVID-19, H5N1 (and other avian influenza variants), as well as vector-borne viruses with pandemic potential (Zika, Nipah, and others) (Jones et al., 2008; Salyer et al., 2017; Marani et al., 2021; Bernstein et al., 2022; Holmes, 2022). These diseases pose an increasing and critical threat to global health and economic security. The June 2021 report of a high-level G20 panel posits that "We are in an age of pandemics.... There is every likelihood that the next pandemic will come within a decade — arising from a novel influenza strain, another coronavirus, or one of several other dangerous pathogens. Its impact on human health and the global economy could be even more profound than that of COVID-19." Hence, response to pandemic threats requires planning scenarios that address the joint problem of mitigating transmission risk while minimizing socioeconomic impacts. For example, a study preceding the COVID-19 pandemic estimated that pandemic impacts might approach 500 billion dollars per year (0.6% of global income) (Fan et al., 2018). In fact, GDP decreased by ≈3% in 2020, or approximately 2.5 trillion dollars (Gagnon et al., 2023),

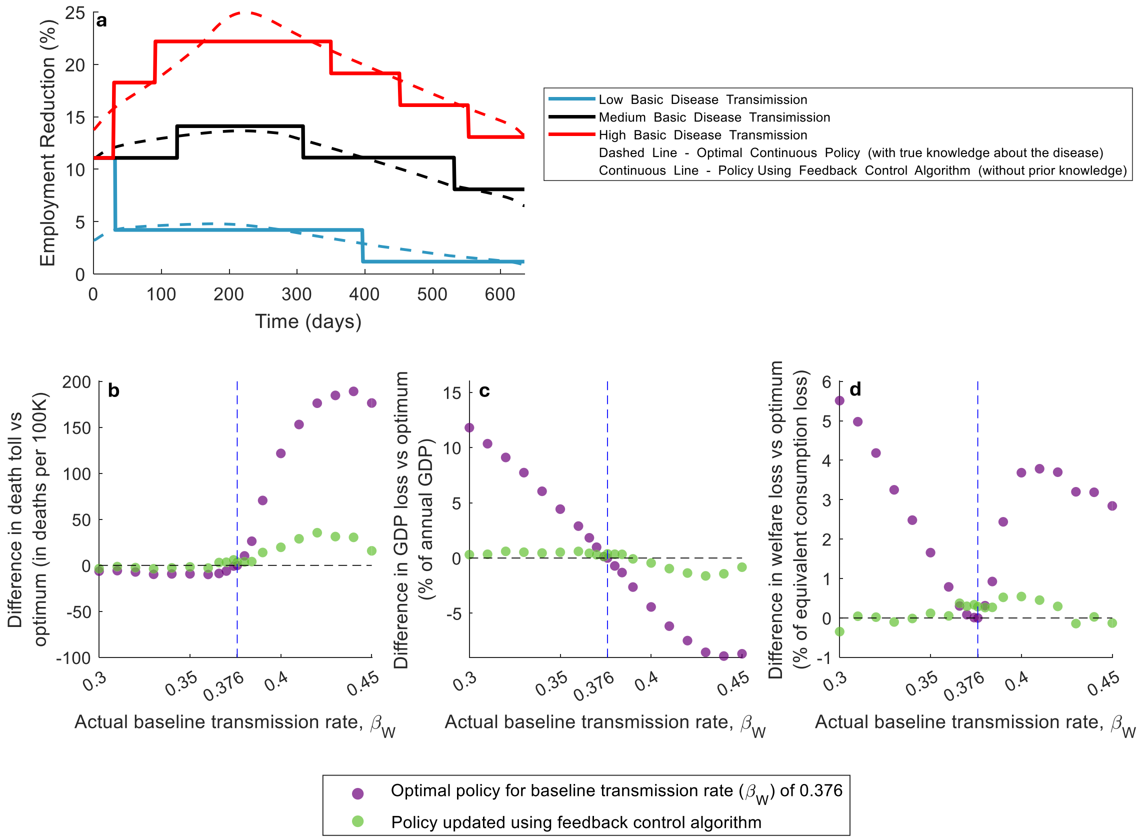

Fig. 4. Comparison of epidemic outcomes given social planning policy guided by feedback, closed-loop control vs. open loop control. (a) Employment reduction policies in the case of low, medium, and high disease transmission respectively. The curves contrast the optimal, open-loop continuous policies given accurate knowledge of the disease state (dashed line) with a feedback, closed-loop control policy that does not use direct information about the disease state (solid line). Impact of misspecification of disease parameters given variation in the basic transmission level, β_W, given differences in (b) death toll, (c) GDP loss, and (d) relative change in WL. The optimal policy is highly sensitive to misspecification of disease transmission rates, whereas the feedback control policy approach is not. The feedback policy maintains low levels of death, GDP loss, and overall welfare loss across different estimates of disease strength during planning.

consistent with interquartile range estimates of 2.6%–4.2% total GDP loss per year due to global warming by 2050 under a 1.5 °C increase scenario (IPCC, 2023). There is a clear need to leverage lessons learned from the COVID-19 response and improve public health infrastructure. However, social fatigue, the spread of misinformation, and politicization of public health response each presents challenges to coordinated responses if a novel threat were to arise.

Here, the social planning response is guided by an idealized model of disease spread coupled to an economic model. Both the economic and epidemic model come with caveats. The epidemic model is based on a SEIR model, an intentional oversimplification of complex disease dynamics. Nonetheless, SEIR models or variants, including branching process models, have features that closely resemble those in real outbreaks (e.g., unimodal generation interval distributions) and are often utilized in response to a novel outbreak (Park et al., 2020a; Read et al., 2021). An important priority for future work is to evaluate the dynamics of policy recommendations as parameter estimates and model structure change during an outbreak. Changes may reflect recognition of risk-stratification (Britton et al., 2020; Rose et al., 2021; Berestycki et al., 2021; Gomes et al., 2022; Berestycki et al., 2023), better-performing models within a forecast hub (Cramer et al., 2022), and updates to core transmission routes that inform intervention strategies (Gandhi et al., 2020; Morawska and Milton, 2020). Extensions should also address differential impacts on distinct regions (Kortessis et al., 2020) especially when projecting from beyond the initial outbreak phase (Kissler et al., 2020). Likewise, the economic model is simplified. It can be extended by modeling the heterogeneity of individuals (Brotherhood et al., 2024) and of firms or sectors (Kaplan et al., 2020), explicit modeling of costs to policy implementation (Du et al., 2025), and the formulation of learning mechanisms (Eichenbaum et al., 2024). Likewise the epidemic model includes a relatively simplified representation of outbreak dynamics. The model neglects differences in asymptomatic, presymptomatic, and symptomatic transmission, does not account for age–structure or heterogeneous mixing, stochasticity, evolution of strains, nor spatially explicit dynamics arising from a combination of long-distance travel and local mobility patterns. Nonetheless, the framework presented here could be adapted to variations of both the economic and/or epidemic components of the model. In doing so, it will be essential to consider to what extent social planning is feasible, improves upon expected endogenous responses to epidemics, and does not unintentionally induce increases in welfare loss.

We anticipate that efforts to extend the social planning framework in this paper to other epi-economic contexts will face similar tensions in efforts to minimize the conflicting costs of the economy vs. mortality and morbidity in the population. Here, we focused on a control theoretic-approach to policy intervention that modulated activity rates. By comparison, Du et al. (2025) evaluated the behavior of heterogeneous agents optimizing dynamic labor/work decisions under infection risk and focus on behavioral heterogeneity and policy scenarios rather than on a formal social-planner welfare-loss control problem. Likewise, Boucekkine et al. (2024) systematize the field's conceptual and mathematical challenges (non-convex disease dynamics, existence/sufficiency in optimal control), but do not propose a concrete feedback policy. Bonnet et al. (2024) map four model families and identify limited coverage of disparities and poverty and limited developing-country focus. Finally, Haw et al. (2022) formalize the causal study of econo-epidemics and enumerate key dataset and constraint needs to advance this interface. We note that policy interventions could include a broader range of options such as paid medical leave and direct financial incentives, as in a recent study (Du et al., 2025). We caution that strict use of open-loop control may remain sensitive to misspecification of parameters associated with disease and behavioral feedback. Instead, we advocate a multi-step strategy. First, open-loop control can be used to identify a measurable proxy (e.g., here we focus on the effective reproduction number of the disease Gostic et al., 2020) to achieve desired outcomes (e.g., minimizing welfare loss). Then, the optimal policy can be computed by feedback control such that the goal of policy interventions is to aim the measured, effective reproduction number to a given target value. The advantage of the closed-loop control system over that of the open-loop control is its robustness to parameter misspecification. The robustness in a closed-loop setting is made possible by the flow of information from the realized dynamics (and its deviation from expected dynamics) back to the social planner. The flow of real-time information is absent in open-loop scenarios. This robustness represents a strong rationale for consideration of closed-loop control approaches for policy interventions in practice.

In closing, consistent with prior work focusing on control strategies to manage COVID-19 epidemic dynamics (in the absence of socioeconomic feedback Morris et al., 2021; Castro et al., 2020) we find that optimal dynamic control policies are highly sensitive to misspecification of parameters and dynamics, lead to mistimed interventions, and increases in welfare loss. Although feedback control policies are robust to the assumptions and feedback in the present econo-epidemic framework, it will be essential to evaluate robustness to structural and parameter uncertainty in more complex models moving forward (Du et al., 2025). Implementing policies that reduce welfare loss also depends on the extent to which individuals take steps to reduce transmission in response to perceived risk of infection. Increasing polarization (Leonard et al., 2021) and/or social conformity (Morsky et al., 2023) could limit the effectiveness of endogenous responses, thereby increasing the need for intervention policies, while at the same time undermining the effectiveness of policies. We recommend that efforts to communicate optimal feedback control policies prioritize communication of the benefits and rationale behind policies — both in terms of public health and socioeconomic benefits. Doing so will not just require development of more sophisticated models, but an increasing willingness to collaborate across social sciences, economics, and public health.

CRediT authorship contribution statement

Ofer Cornfeld: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Conceptualization. **Kaicheng Niu:** Writing – review & editing, Software, Methodology, Investigation. **Oded Neeman:** Writing – review & editing, Visualization, Software, Methodology, Investigation. **Michael Roswell:** Writing – review & editing, Visualization. **Gabi Steinbach:** Writing – review & editing, Visualization. **Stephen J. Beckett:** Writing – review & editing, Visualization. **Yorai Wardi:** Writing – review & editing, Validation, Software, Methodology, Formal analysis, Conceptualization. **Joshua S. Weitz:** Writing – review & editing, Writing – original draft, Visualization, Supervision, Project administration, Investigation, Funding acquisition, Conceptualization. **Eran Yashiv:** Writing – review & editing, Writing – original draft, Visualization, Supervision, Resources, Project administration, Methodology, Investigation.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Joshua Weitz reports financial support was provided by Simons Foundation. Joshua Weitz reports financial support was provided by Chaires Blaise Pascal program, Île-de-France. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

We gratefully acknowledge funding from the Simons Foundation, United States grant 930382 (to JSW) and support from the Chaires Blaise Pascal program of the Ile-de-France region (to JSW). SJB and JSW are investigators at the University of Maryland-Institute for Health Computing, which is supported by funding from Montgomery County, Maryland and The University of Maryland Strategic Partnership: MPowering the State, a formal collaboration between the University of Maryland, College Park and the University of Maryland, Baltimore. We thank M. Hochberg and B. Moll for feedback at an early stage of development of this project, and participants at the Brin Mathematics Research Center workshop on Disease Dynamics and Human behavior that took place in November 2024 at the University of Maryland, College Park for useful conversations and feedback and the support of the Research Development Office at the University of Maryland for support in graphics development.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.epidem.2025.100873.

Data availability

All code and simulation data is available at https://github.com/odedneeman/Optimal-Pandemic-Control and archived via zenodo.org Cornfeld et al. (2025).

References

Amiti, M., Heise, S., Karahan, F., Şahin, A., 2024. Inflation strikes back: The role of import competition and the labor market. NBER Macroecon. Annu. 38 (1), 71–131.

Atkeson, A., 2021. Behavior and the Dynamics of Epidemics. Working Paper Series 28760, National Bureau of Economic Research, URL http://www.nber.org/papers/w28760.

Atkeson, A.G., Kopecky, K., Zha, T., 2021. Behavior and the transmission of COVID-19. AEA Pap. Proc. (ISSN: 2574-0776) 111, 356–360. http://dx.doi.org/10.1257/pandp.20211064.

Autor, D., Dube, A., McGrew, A., 2023. The Unexpected Compression: Competition at Work in the Low Wage Labor Market. Working Paper Series 31010, National Bureau of Economic Research, URL http://www.nber.org/papers/w31010.

Berestycki, H., Desjardins, B., Heintz, B., Oury, J.-M., 2021. Plateaus, rebounds and the effects of individual behaviours in epidemics. Sci. Rep. 11 (1), 18339.

Berestycki, H., Desjardins, B., Weitz, J.S., Oury, J.-M., 2023. Epidemic modeling with heterogeneity and social diffusion. J. Math. Biol. (ISSN: 1432-1416) 86 (4), http://dx.doi.org/10.1007/s00285-022-01861-w.

Bernstein, A.S., Ando, A.W., Loch-Temzelides, T., Vale, M.M., Li, B.V., Li, H., Busch, J., Chapman, C.A., Kinnaird, M., Nowak, K., Castro, M.C., Zambrana-Torrelio, C., Ahumada, J.A., Xiao, L., Roehrdanz, P., Kaufman, L., Hannah, L., Daszak, P., Pimm, S.L., Dobson, A.P., 2022. The costs and benefits of primary prevention of zoonotic pandemics. Sci. Adv. (ISSN: 2375-2548) 8 (5), http://dx.doi.org/10.1126/sciadv.abl4183.

Bonnet, G., Pearson, C.A.B., Torres-Rueda, S., Ruiz, F., Lines, J., Jit, M., et al., 2024. A scoping review and taxonomy of epidemiological-macroeconomic models of COVID-19. Value Health 27, 104–116, URL https://www.valueinhealthjournal.com/article/S1098-3015(23)06154-5/fulltext.

Boucekkine, R., Chakraborty, S., Goenka, A., Liu, L., 2024. Economic epidemiological modelling: A progress report. J. Math. Econom. 113, 103011, URL https://www.sciencedirect.com/science/article/pii/S0304406824000703.

Britton, T., Ball, F., Trapman, P., 2020. A mathematical model reveals the influence of population heterogeneity on herd immunity to SARS-CoV-2. Science (ISSN: 1095-9203) 369 (6505), 846–849. http://dx.doi.org/10.1126/science.abc6810.

Brotherhood, L., Kircher, P., Santos, C., Tertilt, M., 2024. Optimal Age-based Policies for Pandemics: An Economic Analysis of Covid-19 and Beyond. Working Paper Series 32558, National Bureau of Economic Research, URL http://www.nber.org/papers/w32558.

Castro, M., Ares, S., Cuesta, J.A., Manrubia, S., 2020. The turning point and end of an expanding epidemic cannot be precisely forecast. Proc. Natl. Acad. Sci. 117 (42), 26190–26196.

Christakis, N., 2020. Apollo's Arrow: The Profound and Enduring Impact of Coronavirus on the Way We Live. Little Brown, New York, NY.

Cornfeld, O., Niu, K., Neeman, O., Roswell, M., Steinbach, G., Beckett, S.J., Wardi, Y., Weitz, J.S., Yashiv, E., 2025. Code for "Integrating Macroeconomic and Public Health Impacts in Designing Social Planning Policies for Pandemic Response". Zenodo, http://dx.doi.org/10.5281/zenodo.14714610.

Cramer, E.Y., Ray, E.L., Lopez, V.K., Bracher, J., Brennen, A., Castro Rivadeneira, A.J., Gerding, A., Gneiting, T., House, K.H., Huang, Y., et al., 2022. Evaluation of individual and ensemble probabilistic forecasts of COVID-19 mortality in the United States. Proc. Natl. Acad. Sci. 119 (15), e2113561119.

Du, Z., Wang, Y., Bai, Y., Wang, L., Cowling, B.J., Meyers, L.A., 2023. Estimate of COVID-19 deaths, China, December 2022–February 2023. Emerg. Infect. Dis. 29 (10), 2121.

Du, H., Zahn, M.V., Loo, S.L., Alleman, T.W., Truelove, S., Patenaude, B., Gardner, L.M., Papageorge, N., Hill, A.L., 2025. Improving policy design and epidemic response using integrated models of economic choice and disease dynamics with behavioral feedback. PLoS Comput. Biol. 21 (10), e1013549.

Eichenbaum, M., Godinho de Matos, M., Lima, F., Rebelo, S., Trabandt, M., 2024. Expectations, infections, and economic activity. J. Political Econ. 132 (8), 2571–2611. http://dx.doi.org/10.1086/729449.

Fan, V.Y., Jamison, D.T., Summers, L.H., 2018. Pandemic risk: how large are the expected losses? Bull. World Health Organ. (ISSN: 0042-9686) 96 (2), 129–134. http://dx.doi.org/10.2471/blt.17.199588.

Ferguson, N., Laydon, D., Nedjati-Gilani, G., Imai, N., Ainslie, K., Baguelin, M., Bhatia, S., Boonyasiri, A., Cucunubá, Z., Cuomo-Dannenburg, G., et al., 2020. Report 9: Impact of non-pharmaceutical interventions (NPIs) to reduce COVID19 mortality and healthcare demand. Imp. Coll. Lond. 10 (77482), 491–497.

Flaxman, S., Mishra, S., Gandy, A., Unwin, H.J.T., Mellan, T.A., Coupland, H., Whittaker, C., Zhu, H., Berah, T., Eaton, J.W., et al., 2020. Estimating the effects of non-pharmaceutical interventions on COVID-19 in Europe. Nature 584 (7820), 257–261.

Franklin, G., Powell, J., Emami-Naeini, A., 2019. Feedback Control of Dynamic Systems, eighth ed. Pearson, New York, NY.

Gagnon, J.E., Kamin, S.B., Kearns, J., 2023. The impact of the COVID-19 pandemic on global GDP growth. J. Jpn. Int. Econ. 68, 101258.

Gandhi, M., Yokoe, D.S., Havlir, D.V., 2020. Asymptomatic transmission, the Achilles' heel of current strategies to control Covid-19. N. Engl. J. Med. 382 (22), 2158–2160.

Gomes, M.G.M., Ferreira, M.U., Corder, R.M., King, J.G., Souto-Maior, C., Penha-Gonçalves, C., Gonçalves, G., Chikina, M., Pegden, W., Aguas, R., 2022. Individual variation in susceptibility or exposure to SARS-CoV-2 lowers the herd immunity threshold. J. Theoret. Biol. (ISSN: 0022-5193) 540, 111063. http://dx.doi.org/10.1016/j.jtbi.2022.111063.

Gostic, K.M., McGough, L., Baskerville, E.B., Abbott, S., Joshi, K., Tedijanto, C., Kahn, R., Niehus, R., Hay, J.A., De Salazar, P.M., Hellewell, J., Meakin, S., Munday, J.D., Bosse, N.I., Sherrat, K., Thompson, R.N., White, L.F., Huisman, J.S., Scire, J., Bonhoeffer, S., Stadler, T., Wallinga, J., Funk, S., Lipsitch, M., Cobey, S., 2020. Practical considerations for measuring the effective reproductive number, Rt. In: Pitzer, V.E. (Ed.), PLoS Comput. Biol. (ISSN: 1553-7358) 16 (12), e1008409. http://dx.doi.org/10.1371/journal.pcbi.1008409.

Harding, M., Lindé, J., Trabandt, M., 2023. Understanding post-COVID inflation dynamics. J. Monet. Econ. (ISSN: 0304-3932) 140, S101–S118. http://dx.doi.org/10.1016/j.jmoneco.2023.05.012.

Haw, D.J., Morgenstern, C., Forchini, G., Johnson, R., Doohan, P., Smith, P.C., et al., 2022. Data needs for integrated economic-epidemiological models of pandemic mitigation policies. Epidemics 41, 100644, URL https://www.ncbi.nlm.nih.gov/pmc/articles/PMC9624062/.

Hellewell, J., Abbott, S., Gimma, A., Bosse, N.I., Jarvis, C.I., Russell, T.W., Munday, J.D., Kucharski, A.J., Edmunds, W.J., Sun, F., et al., 2020. Feasibility of controlling COVID-19 outbreaks by isolation of cases and contacts. Lancet Glob. Health 8 (4), e488–e496.

Holmes, E.C., 2022. The ecology of viral emergence. Annu. Rev. Virol. 9 (1), 173–192.

Hsiang, S., Allen, D., Annan-Phan, S., Bell, K., Bolliger, I., Chong, T., Druckenmiller, H., Huang, L.Y., Hultgren, A., Krasovich, E., Lau, P., Lee, J., Rolf, E., Tseng, J., Wu, T., 2020. The effect of large-scale anti-contagion policies on the COVID-19 pandemic. Nature (ISSN: 1476-4687) 584 (7820), 262–267. http://dx.doi.org/10.1038/s41586-020-2404-8.

IPCC, 2023. Climate change 2022: Mitigation of climate change. Contribution of working group III to the sixth assessment report of the intergovernmental panel on climate change. Cambridge University Press, ISBN: 9781009157926, http://dx.doi.org/10.1017/9781009157926,

Jones, K.E., Patel, N.G., Levy, M.A., Storeygard, A., Balk, D., Gittleman, J.L., Daszak, P., 2008. Global trends in emerging infectious diseases. Nature (ISSN: 1476-4687) 451 (7181), 990–993. http://dx.doi.org/10.1038/nature06536.

Jordà, Ò., Singh, S.R., Taylor, A.M., 2022. Longer-run economic consequences of pandemics. Rev. Econ. Stat. (ISSN: 1530-9142) 104 (1), 166–175. http://dx.doi.org/10.1162/rest_a_01042.

Kaplan, G., Moll, B., Violante, G.L., 2020. The Great Lockdown and the Big Stimulus: Tracing the Pandemic Possibility Frontier for the U.S.. Working Paper Series 27794, National Bureau of Economic Research, URL http://www.nber.org/papers/w27794.

Kissler, S.M., Tedijanto, C., Goldstein, E., Grad, Y.H., Lipsitch, M., 2020. Projecting the transmission dynamics of SARS-CoV-2 through the postpandemic period. Science 368 (6493), 860–868.

Kortessis, N., Simon, M.W., Barfield, M., Glass, G.E., Singer, B.H., Holt, R.D., 2020. The interplay of movement and spatiotemporal variation in transmission degrades pandemic control. Proc. Natl. Acad. Sci. 117 (48), 30104–30106.

Leonard, N.E., Lipsitz, K., Bizyaeva, A., Franci, A., Lelkes, Y., 2021. The nonlinear feedback dynamics of asymmetric political polarization. Proc. Natl. Acad. Sci. 118 (50), e2102149118.

Macedo, S., Lee, F., 2025. In Covid's Wake: How Our Politics Failed Us. Princeton University Press, ISBN: 9780691267142, URL http://www.jstor.org/stable/jj.19583515.

Marani, M., Katul, G.G., Pan, W.K., Parolari, A.J., 2021. Intensity and frequency of extreme novel epidemics. Proc. Natl. Acad. Sci. (ISSN: 1091-6490) 118 (35), http://dx.doi.org/10.1073/pnas.2105482118.

McBain, R.K., Cantor, J.H., Jena, A.B., Pera, M.F., Bravata, D.M., Whaley, C.M., 2021. Decline and rebound in routine cancer screening rates during the COVID-19 pandemic. J. Gen. Intern. Med. 36, 1829–1831.

Morawska, L., Milton, D.K., 2020. It is time to address airborne transmission of COVID-19. Clin. Infect. Dis.: An Off. Publ. Infect. Dis. Soc. Am. ciaa939.

Moreno, C., Wykes, T., Galderisi, S., Nordentoft, M., Crossley, N., Jones, N., Cannon, M., Correll, C.U., Byrne, L., Carr, S., et al., 2020. How mental health care should change as a consequence of the COVID-19 pandemic. Lancet Psychiatry 7 (9), 813–824.

Morris, D.H., Rossine, F.W., Plotkin, J.B., Levin, S.A., 2021. Optimal, near-optimal, and robust epidemic control. Commun. Phys. 4 (1), 78. http://dx.doi.org/10.1038/s42005-021-00570-y.

Morsky, B., Magpantay, F., Day, T., Akçay, E., 2023. The impact of threshold decision mechanisms of collective behavior on disease spread. Proc. Natl. Acad. Sci. 120 (19), e2221479120.

Park, S.W., Bolker, B.M., Champredon, D., Earn, D.J., Li, M., Weitz, J.S., Grenfell, B.T., Dushoff, J., 2020a. Reconciling early-outbreak estimates of the basic reproductive number and its uncertainty: framework and applications to the novel coronavirus (SARS-CoV-2) outbreak. J. R. Soc. Interface 17 (168), 20200144.

Park, S.W., Cornforth, D.M., Dushoff, J., Weitz, J.S., 2020b. The time scale of asymptomatic transmission affects estimates of epidemic potential in the COVID-19 outbreak. Epidemics (ISSN: 1755-4365) 31, 100392. http://dx.doi.org/10.1016/j.epidem.2020.100392.

Read, J.M., Bridgen, J.R., Cummings, D.A., Ho, A., Jewell, C.P., 2021. Novel coronavirus 2019-nCoV (COVID-19): early estimation of epidemiological parameters and epidemic size estimates. Philos. Trans. R. Soc. B 376 (1829), 20200265.

Rose, C., Medford, A.J., Goldsmith, C.F., Vegge, T., Weitz, J.S., Peterson, A.A., 2021. Heterogeneity in susceptibility dictates the order of epidemic models. J. Theoret. Biol. 528, 110839.

Salyer, S.J., Silver, R., Simone, K., Barton Behravesh, C., 2017. Prioritizing zoonoses for global health capacity building—Themes from one health zoonotic disease workshops in 7 countries, 2014–2016. Emerg. Infect. Dis. (ISSN: 1080-6059) 23 (13), http://dx.doi.org/10.3201/eid2313.170418.

Simon, N.B., Dockins, C., Maguire, K.B., Newbold, S.C., Krupnick, A.J., Taylor, L.O., 2019. Policy brief—What's in a name? A search for alternatives to "vsl". Rev. Environ. Econ. Policy 13, 155–161.

Weitz, J.S., Park, S.W., Eksin, C., Dushoff, J., 2020. Awareness-driven behavior changes can shift the shape of epidemics away from peaks and toward plateaus, shoulders, and oscillations. Proc. Natl. Acad. Sci. 117 (51), 32764–32771.

Williams, J., Reis, R., 2024. Connecting academics to policy: A conversation with New York Fed President John C. Williams. URL https://www.youtube.com/watch?v=688mDeSlTU4.