

Private Choices in Public Health: A Framework for Economic Epidemiological
Modeling of Infectious Disease

Jose Felipe Montano-Campos

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Reading Committee:

Anirban Basu, Chair

Kyu Eun Lee

Blythe Adamson

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Jose Felipe Montano-Campos

University of Washington

Abstract

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Jose Felipe Montano-Campos

Chair of the Supervisory Committee:

Anirban Basu

Department of Pharmacy

This dissertation investigates the role of risk compensation in infectious disease dynamics by examining how individuals adjust private preventive behaviors in response to perceived mortality risk, and how these behavioral shifts shape and are shaped by epidemic trajectories. While conventional epidemiological models assume fixed or policy-driven contact rates, real-world transmission depends critically on how individuals perceive and respond to evolving risk. Public health policies, in turn, interact with these private behaviors—amplifying or dampening their effects.

The first part of this dissertation provides empirical evidence of risk compensation behavior by analyzing high-frequency mobility data across U.S. counties during the COVID-19 pandemic. Using lagged local mortality as a proxy for perceived risk, the study finds that individuals significantly reduced their mobility in response to rising deaths—particularly in high-contact,

discretionary domains. These responses evolved over time and were shaped by public health interventions such as shelter-in-place orders and mask mandates, which often amplified rather than displaced private behavioral changes.

The second part develops a dynamic economic-epidemiological model that endogenizes contact rates through mortality-responsive behavioral feedback. Critically, the magnitude of behavioral responsiveness estimated in the empirical analysis is used to calibrate the strength of the feedback loop—bridging observed behavior with modeled transmission. This endogenous co-evolution of behavior and epidemic severity creates a self-regulating system in which private action dynamically responds to real-time risk signals, suppressing transmission as perceived threat intensifies. The model, grounded in a delayed SEIRDS framework, demonstrates how such feedback can flatten epidemic curves, delay transmission peaks, and produce multiple waves. Introducing pandemic fatigue—modeled as declining responsiveness to risk—erodes this adaptive loop, weakening the self-limiting dynamic and enabling persistent spread. Simulations highlight the importance of accounting for behavioral adaptation in forecasting and policy design.

Together, these studies offer a unified framework for understanding how private choices interact with public policy and disease dynamics through the lens of risk perception and behavioral adaptation.

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Chapter 1: INTRODUCTION

Individual behavior plays a pivotal role in shaping the trajectory of infectious disease outbreaks. Yet, traditional epidemiological models and much of public health policymaking continue to treat human behavior as fixed or purely reactive to formal interventions. In reality, individuals actively assess and respond to changing conditions—modifying their preventive behaviors based on perceived levels of threat. This dynamic feedback between perceived risk and private action is at the heart of risk compensation, a behavioral phenomenon in which people reduce or increase preventive efforts depending on how risky they believe the environment to be.

This dissertation develops a conceptual and analytical framework that captures the endogenous nature of human behavior in the context of infectious disease—where private preventive actions evolve in response to shifting perceived risk and feed back into transmission dynamics. Within this broader agenda, the COVID-19 pandemic offers a unique and timely natural experiment. The unprecedented availability of granular, real-time data on disease severity, policy interventions, and human mobility provides a rich empirical setting to observe how individuals adjust their behavior in response to changing risk. While COVID-19 serves as the empirical foundation, the behavioral mechanisms and modeling approaches developed here are designed to generalize beyond this specific context.

The work proceeds in two parts. The first provides empirical evidence of risk compensation by analyzing high-frequency mobility data across U.S. counties during the COVID-19 pandemic.

Using lagged local mortality as a proxy for perceived risk, I found that individuals significantly reduced their mobility in response to rising deaths—particularly in discretionary, high-contact settings. These behavioral responses varied across time and space and were shaped by public health interventions, such as shelter-in-place orders and mask mandates. Rather than crowding out private action, these policies often amplified it, revealing an important interaction between public mandates and endogenous preventive behavior.

The second part of the dissertation formalizes these behavioral insights in a dynamic epidemic model. I developed a modified SEIRDS framework in which the contact rate is endogenized—declining as perceived mortality risk rises. The strength of this behavioral feedback is calibrated using the empirical responsiveness estimated in the first part, providing a direct bridge between observed behavior and theoretical transmission dynamics. This endogenous co-evolution of behavior and epidemic severity creates a self-regulating system in which private action dynamically responds to real-time risk signals, suppressing transmission as perceived threat intensifies. However, the model also incorporates pandemic fatigue, conceptualized as a diminishing responsiveness to ongoing risk, which gradually erodes the strength of this adaptive feedback loop. As behavioral vigilance fades, contact rates begin to rise even in the face of persistent mortality, enabling renewed waves of transmission.

By integrating empirically grounded behavioral responses into a formal transmission model, this dissertation offers a unified framework for understanding how private choices and public policies jointly shape epidemic outcomes. It contributes to the literature by combining real-world

behavioral measurement with dynamic modeling, demonstrating both the strength and fragility of behavioral adaptation in public health. In doing so, it highlights the importance of embedding behavioral realism into epidemic forecasting and policy design—especially in prolonged public health crises where perception, fatigue, and adaptation evolve over time.

Chapter 2: RISK PERCEPTION AND PREVENTIVE BEHAVIOR: EVIDENCE OF RISK COMPENSATION DURING THE COVID-19 PANDEMIC

2.1 Abstract

Risk compensation refers to the phenomenon in which individuals endogenously adjust private preventive behaviors in response to perceived risk. Leveraging the COVID-19 pandemic as a natural experiment, we examined how risk perception shaped preventive behavior across U.S. counties. We proxy risk perception using local COVID-19 mortality, a salient and objective risk signal, and analyze over 1.1 million daily observations from 1,206 counties, where preventive behavior is measured through changes in mobility. Using a fixed effects regression framework, we controlled for behavioral persistence, unobserved county-level differences, and seasonal variation in mobility. We found that an additional death per 10,000 population is associated with a 9.7% reduction in total mobility ($p < 0.001$). This behavioral reaction is amplified by public health interventions: shelter-in-place orders increase the behavioral response by an additional 8.7% ($p < 0.001$), and mask mandates by 4.3% ($p = 0.012$). The response also attenuates over time, declining by 1.0 percentage point per month ($p < 0.001$), consistent with behavioral normalization or pandemic fatigue. To further unpack the nature of private preventive behavior, we examined category-specific mobility patterns. As a response to perceived risk, we found sharp declines in high-contact, discretionary activities such as Retail & Recreation (-7.3% , $p < 0.001$) and Transit (-8.0% , $p < 0.001$), smaller reductions in essential activities like Grocery & Pharmacy (-1.2% , $p = 0.001$), no significant change in Parks ($+0.3\%$, $p = 0.901$), and an increase in Residential mobility ($+1.7\%$, $p < 0.001$), reflecting home-based risk avoidance. By controlling for formal policies and behavioral inertia, we isolate the effect of mortality-driven risk

perception on the demand for private preventive measures-advancing the literature on endogenous behavioral response and risk compensation using uniquely granular data.

2.2 Introduction

In public health crises, individual behavior is not merely reactive—it is endogenous, shaped by evolving perceptions of risk. Understanding how individuals adjust their private preventive behaviors and voluntary actions to reduce infection risk in response to evolving health risks is critical for managing infectious disease outbreaks and designing effective public health policies. The COVID-19 pandemic represents an unprecedented natural experiment, exposing communities worldwide to rapidly changing and obvious health risks, thus providing a unique opportunity to study endogenous dynamic behavioral responses to risk signals empirically. The economic principle of risk compensation is central to understanding these responses, describing how individuals adjust their private preventive behaviors in response to perceived risk. In this paper, we study how local observed mortality signals influence private preventive behaviors, specifically reductions in mobility, presumably through forming individual risk perceptions. Our central focus is on endogenous behavioral responses that operate alongside, and sometimes independently from, formal public health policies. The presence of such private endogenous behavior has long been theorized in the economics literature ¹; however, it has not been comprehensively studied empirically in the context of Covid.

Acknowledging the critical role of complex behavioral trade-offs and risk compensation is important for accurately evaluating public health policies and intervention effectiveness ²⁻⁴. The success of public health policies fundamentally hinges on accurately predicting human behavior. Policy interventions and individual actions are interdependent, dynamically influencing each

other. Yet policy design frequently assumes stable or predictable behavioral responses. As articulated by the Lucas critique, once a policy is implemented, individuals rapidly adjust their beliefs, expectations, and behaviors, resulting in unforeseen outcomes. Traditional epidemiological models deployed during the Covid times often assumed static or constant transmission rates, neglecting the dynamic nature of human behavior and risk perception adjustments. This oversight can lead to serious unintended consequences, including misestimations in the effectiveness of disease control measures. Specifically, the effectiveness of policy can be overestimated if models fail to account for declining demand for preventive measures as perceived risk decreases, leading to an inflated expectation of long-term impact. Conversely, effectiveness can be underestimated if interventions overlook heterogeneous behavioral responses, assuming uniform reactions across diverse populations. Such oversimplifications ignore critical behavioral complexities and risk compensation effects, weakening policy outcomes and public health strategies. For example, COVID-19 shelter-in-place orders initially led to significant mobility reductions, but compliance waned over time as risk perceptions adjusted. Neglecting to anticipate these behavioral adaptations can dramatically undermine policy effectiveness, prolong outbreaks, and elevate public health risks. Thus, rigorously studying how individuals adjust behaviors in response to evolving risk signals is very important for creating robust and responsive public health interventions.

Previous evidence across multiple health interventions consistently highlights the presence of risk compensation behaviors. In infectious disease prevention, studies of HIV pre-exposure prophylaxis (PrEP) clearly demonstrate that users significantly increase condomless sex and experience higher STI incidence after starting treatment ⁵. Similarly, Lakdawalla et al. (2006) observed substantial increases in sexual risk-taking behaviors following HIV treatment

breakthroughs, suggesting that improved survival expectations directly motivated riskier behaviors ^{6,7}. Chan (2016) further demonstrated significant behavioral shifts toward riskier sexual practices due to perceptions of lower infection risk from HIV treatments ⁸.

Risk compensation behaviors are also evident in the broader context of the COVID-19 pandemic. For instance, Jia et al. (2022) found that following vaccination, individuals in the U.S. significantly reduced protective behaviors such as mask-wearing and social distancing ⁹. Similarly, a global analysis covering 107 countries showed that higher vaccination rates correlated with increased mobility in retail, recreational, and transit locations, partially offsetting the vaccines' intended public health benefits ¹⁰. Wadud (2022) provided additional empirical support by demonstrating increased community mobility and reduced home confinement after mask mandates were imposed in Bangladesh, indicating that perceived protection led to relaxed preventive behaviors ¹¹.

Previous literature exploring risk compensation in health has predominantly focused on behavioral shifts after adopting specific protective measures. In contrast, our study provides a fundamentally novel perspective by examining proactive behavioral responses to plausibly exogenous shifts in an explicit, objective, and universally observable risk signal—COVID-19 mortality rates.

While individuals may receive risk information from multiple sources, mortality signals are among the most salient, objective, and behaviorally influential indicators available during an infectious disease outbreak. Compared to reported incidence rates, which are subject to testing availability, reporting biases, and frequent underestimation, mortality statistics provide a more stable, highly visible, and emotionally resonant measure of disease severity ^{12,13}. Prior literature suggests that individuals respond more strongly to tangible and severe outcomes, such as deaths,

than to abstract case numbers or projections, particularly when information is amplified through media coverage and personal networks^{14,15}. Moreover, deaths represent the ultimate negative health outcome, anchoring perceptions of threat more powerfully than rising case counts alone¹⁶. Therefore, focusing on local observed mortality provides a theoretically grounded and empirically justified proxy for dynamic risk perception, capturing the evolving threat landscape that individuals perceive and to which they adjust their preventive behaviors.

To do so, we used detailed, daily county-level data across the United States, including COVID-19 cases, deaths, and total mobility and across distinct domains—Retail & Recreation, Grocery & Pharmacy, Workplaces, Transit Stations, Parks, and Residential (time spent at home). These mobility patterns capture different dimensions of private preventive behavior, allowing for a nuanced characterization of risk compensation dynamics. We further assessed how these behavioral responses evolve daily and over time as the pandemic progresses. Additionally, we investigated how public health policies, such as shelter-in-place orders and mask mandates, mediate or modify these behavioral adjustments, thereby clarifying the dynamic interplay between evolving risk perceptions and policy-driven preventive strategies.

This study makes three contributions. First, it provides a detailed empirical analysis of dynamic behavioral adjustments driven by explicit and objectively observable risk signals (mortality rates) rather than retrospective shifts after adopting protective measures. Second, our approach accounts explicitly for temporal variations in behavioral responsiveness, highlighting how the sensitivity to risk signals evolves throughout the pandemic's progression. Third, by examining how public health policies shape these reactions, we shed light on the complex interactions between individual and institutional responses. In what follows, we describe our data and

methodological approach, present detailed empirical results, and discuss the policy implications and recommendations arising from our findings.

2.3 Study Timeframe

Our study spans from February 15, 2020, to November 30, 2021, covering key phases of the COVID-19 pandemic in the United States. This timeframe ensures that we capture the evolution of risk perception and preventive behaviors during the pandemic while maintaining a clean analytical period that allows us to assess behavioral responses under a period where vaccines were highly effective before later waves introduced complexities related to waning immunity and variant resistance (Omicron variant).

2.4 Data Sources and Variable Construction

COVID-19 Cases and Deaths

To track the progression of COVID-19 across the United States, we used daily county-level confirmed case and death counts from the Johns Hopkins Coronavirus Resource Center (JHU CRC). The JHU CRC became the primary global repository for real-time infectious disease tracking, aggregating data from 260 sources, including 182 local, state, and federal agencies, such as the Centers for Disease Control and Prevention (CDC), the World Health Organization (WHO), and state health departments. Recognized for its accuracy and reliability, the JHU CRC was named one of TIME Magazine's "Top 100 Inventions of 2020" and received the "Meeting the Moment for Public Health" award from Research!America in 2021, underscoring its critical role in pandemic response and public health research. We apply a seven-day moving average smoothing procedure to account for short-term fluctuations and reporting inconsistencies in daily case and mortality counts. This method stabilizes trends by calculating the mean of reported

values over the previous seven days for each county, reducing noise and improving the accuracy of mortality estimates.

Mobility Data

Data Sources

We utilized two complementary data sources to measure mobility behavior comprehensively:

Google's COVID-19 Community Mobility Reports and SafeGraph Mobility Data.

Google's dataset provides daily, anonymized percentage changes in visits across key categories, including Retail & Recreation, Grocery & Pharmacy, Workplaces, Transit Stations, Parks, and Residential (time spent at home) for the entire study timeframe. These mobility changes are reported relative to a pre-pandemic baseline, which is defined as the median value for each weekday (Monday through Sunday) from January 3 to February 6, 2020. This weekday-specific baseline accounts for systematic differences in movement patterns across days of the week, ensuring that mobility trends are contextualized over time.

SafeGraph tracks mobility using origin-to-destination visits based on anonymized device location data. A visit is recorded when a device remains at both the origin and the destination for at least one minute, ensuring that movement between locations reflects actual visits rather than transient signals. This approach allows for the identification of individual-level mobility trends while preserving privacy. By leveraging aggregated location signals, these mobility data provide insights into patterns of movement and how they change over time in response to external factors such as public health policies and perceived risk.

SafeGraph's dataset, available until March 2021, provides absolute mobility levels at the county level, capturing origin-to-destination visitor flows within counties adjusted for population

distribution. Unlike Google's dataset, which reports percentage changes by location category, SafeGraph offers absolute mobility figures without categorical breakdowns.

Each dataset presents specific limitations. Google's mobility data measures percentage changes relative to a pre-pandemic baseline rather than absolute movement levels. SafeGraph, while providing absolute mobility levels, is restricted to data availability only until March 2021 and lacks category-specific mobility breakdowns. The absence of categorical detail in SafeGraph data is particularly relevant, as different types of mobility reflect distinct private preventive behaviors. Given these constraints, we integrate both datasets to construct a more robust and consistent measure of mobility, leveraging SafeGraph's absolute mobility levels for baseline estimates and Google's category-specific percentage changes for mobility trends across the whole study period.

Integration of Data Sources: Mobility Measurement

To generate a consistent, category-specific measure of absolute mobility, we integrated SafeGraph's total mobility levels with Google's category-specific mobility trends, which report *relative changes* in mobility compared to a pre-pandemic baseline. First, we estimated daily baseline mobility for each county using SafeGraph data from the pre-pandemic period (January 3–February 6, 2020). We then calibrated the fraction of this total baseline mobility allocated to each domain (e.g., Workplaces, Retail & Recreation) using Google's relative mobility trends and SafeGraph data. Because mobility patterns differ between weekdays and weekends, we estimated separate calibrated shares for each: for weekdays, 10% each to Retail & Recreation, Transit, and Grocery & Pharmacy, 64.85% to Workplaces, and 5.06% to Parks; for weekends, shares shift to 15.29% for Retail & Recreation, 15.13% for Grocery & Pharmacy, 17.69% for Transit, 46.82% for Workplaces, and 5.07% for Parks. Finally, we apply Google's daily percentage changes to

these calibrated baselines to reconstruct daily absolute mobility by category across the study period. This method ensures internal consistency and captures meaningful variation across both time and activity type, while enabling us to recover absolute, daily mobility levels by category—a critical feature for analyzing the intensity and timing of private preventive behaviors across distinct domains, each representing different forms of risk-mitigating action. A detailed explanation of the calibration procedure and validation is provided in the appendix.

Public Health Policy Measures

To account for the impact of public health interventions on private preventive measures, we incorporate two key policy variables in our analysis: Shelter-in-Place Orders and Mask Mandates. Data for these variables are sourced from the COVID-19 State and County Policy Orders dataset, a comprehensive repository maintained by the U.S. Department of Health & Human Services. This dataset compiles daily, county-level records of executive orders, mandates, and ordinances implemented across the United States in response to the COVID-19 pandemic. This dataset enables us to assess temporal and spatial variations in policy stringency. Specifically, it provides precise daily indicators of whether a shelter-in-place order or a mask mandate was active in each county.

Shelter-in-Place (SIP) Orders: SIP orders are government directives requiring residents to remain at home except for essential activities. We defined the variable SIP Active as a binary indicator at the county-day level, set to 1 if a county had an active SIP order on a given day, and 0 otherwise.

Mask Mandates: Mask mandates require individuals to wear face coverings in public settings to mitigate viral transmission. The variable Mask Mandate Active is defined as a binary indicator at the county-day level, equal to 1 if a mask mandate was in effect on a given day, and 0 otherwise.

2.5 Empirical Strategy

Pandemic Period Classification

Given the dynamic nature of the pandemic, we divided our analysis into four distinct stages, reflecting shifts in public knowledge, policy interventions, and individual behavioral responses.

1.- Early Pandemic (February 15 – April 30, 2020): This phase represents the initial period of widespread uncertainty and crisis-driven behavioral responses. The first confirmed COVID-19 case in the United States was reported in Washington State on January 20, 2020. The World Health Organization (WHO) declared a Public Health Emergency of International Concern on January 30, 2020, and officially classified COVID-19 as a pandemic on March 11, 2020. The United States declared a national emergency on March 13, 2020. During this phase, public uncertainty was at its peak, with widespread fear driven by overwhelmed hospitals and a lack of information on the virus's transmission and severity. By the end of April, at the peak, approximately 88.3% of U.S. counties had active shelter-in-place orders, and restrictions were widespread. Mortality rates were high, with an estimated case fatality ratio of ~ 0.05 . Preventive behaviors were driven by general uncertainty rather than calculated risk assessment, as individuals reduced mobility across all domains regardless of risk perception (mortality trends).

2.- Risk Compensation Period (May 1, 2020 – February 28, 2021): As public knowledge of COVID-19 increased, risk perception shifted from generalized fear to a more structured assessment based on real-time mortality trends. During this phase, individuals adjusted their private preventive behaviors in response to evolving risk signals. Policy restrictions also

changed, with shelter-in-place orders declining rapidly in early May, leaving only ~12% of U.S. counties with active orders by June 2020. Individuals' reliance on mortality data to guide risk perception grew as they became more informed^{14–16}. While mobility gradually increased, it remained approximately 20% below pre-pandemic levels, and the case fatality ratio dropped to ~0.01.

3.- Vaccination Rollout / Transitional Period (March 1 – May 31, 2021): By March and April 2021, vaccines became available to all adults in most states, but uptake varied, leading to heterogeneity in behavioral responses. This period represents a transitional phase where behavioral adjustments were less clearly defined, as individuals responded to both increasing vaccine availability and evolving risk perceptions.

4.- Post-Vaccination Phase (June 1 – November 30, 2021): By June 1, 2021, nearly half of the U.S. adult population had received at least one vaccine dose, and coverage continued to expand. Mortality rates remained low during this period, and mobility trends neared pre-pandemic levels. With declining perceived risk, individuals may have reassessed the need for precautionary measures. No counties had active shelter-in-place orders by this stage, and the case fatality ratio had fallen below 0.01.

We conducted our empirical analysis separately for each of these defined stages to examine how risk perception influenced private preventive behaviors throughout the pandemic. Each period represents a distinct behavioral environment shaped by evolving public knowledge, policy interventions, and shifting mortality risks. This categorization allows us to capture how behavioral responses adapted to changing risk perception over time.

Empirical Model and Estimation Strategy

Risk perception plays a fundamental role in shaping individual health behaviors, particularly in the context of infectious disease outbreaks. Economic epidemiology posits that individuals engage in behavioral trade-offs, dynamically adjusting their private preventive measures in response to evolving risk signals.

Our analysis assumes that observed mortality shapes individual behavior by influencing perceived risk. While we do not observe perception directly, we interpret behavioral responses to local mortality as operating through this perception channel. That is, we study how changes in observed mortality are translated into preventive behavior through the mechanism of individual risk perception.

In the case of COVID-19, real-time mortality serves as a highly visible and objective measure of risk, guiding individuals' behavioral adaptations. The underlying principle of risk compensation suggests that as perceived risk increases, individuals take stronger preventive actions—such as reducing mobility—while declining risk perceptions may lead to relaxation of these behaviors. To ensure sufficient data for capturing these dynamic behavioral responses, we restricted our analytic sample to counties that report at least 30 days of mobility and mortality data during the Risk Compensation period. This restriction ensures stable coefficient estimates and minimizes noise from counties with sparse or irregular reporting.

This study conceptualizes mobility as a proxy for the demand for private preventive measures. Reducing mobility represents a voluntary action to mitigate infection risk by minimizing exposure to public spaces. Our main outcome variable is total mobility, aggregating movement in Retail & Recreation, Grocery & Pharmacy, Workplaces, and Transit Stations. However, we exclude mobility in parks, as movement in outdoor environments does not reflect the same risk-

mitigation trade-offs as indoor locations. Reducing mobility in high-contact indoor environments represents a stronger behavioral response to risk, whereas increases in park mobility could indicate behavioral substitution rather than actual risk avoidance. Public health guidance consistently emphasized that parks posed a lower risk of virus transmission, and individuals may have shifted towards outdoor spaces as a safer alternative rather than genuinely reducing mobility. Therefore, excluding park mobility ensures that our measure of private preventive behavior is more directly tied to risk-avoidance behaviors in high-exposure settings.

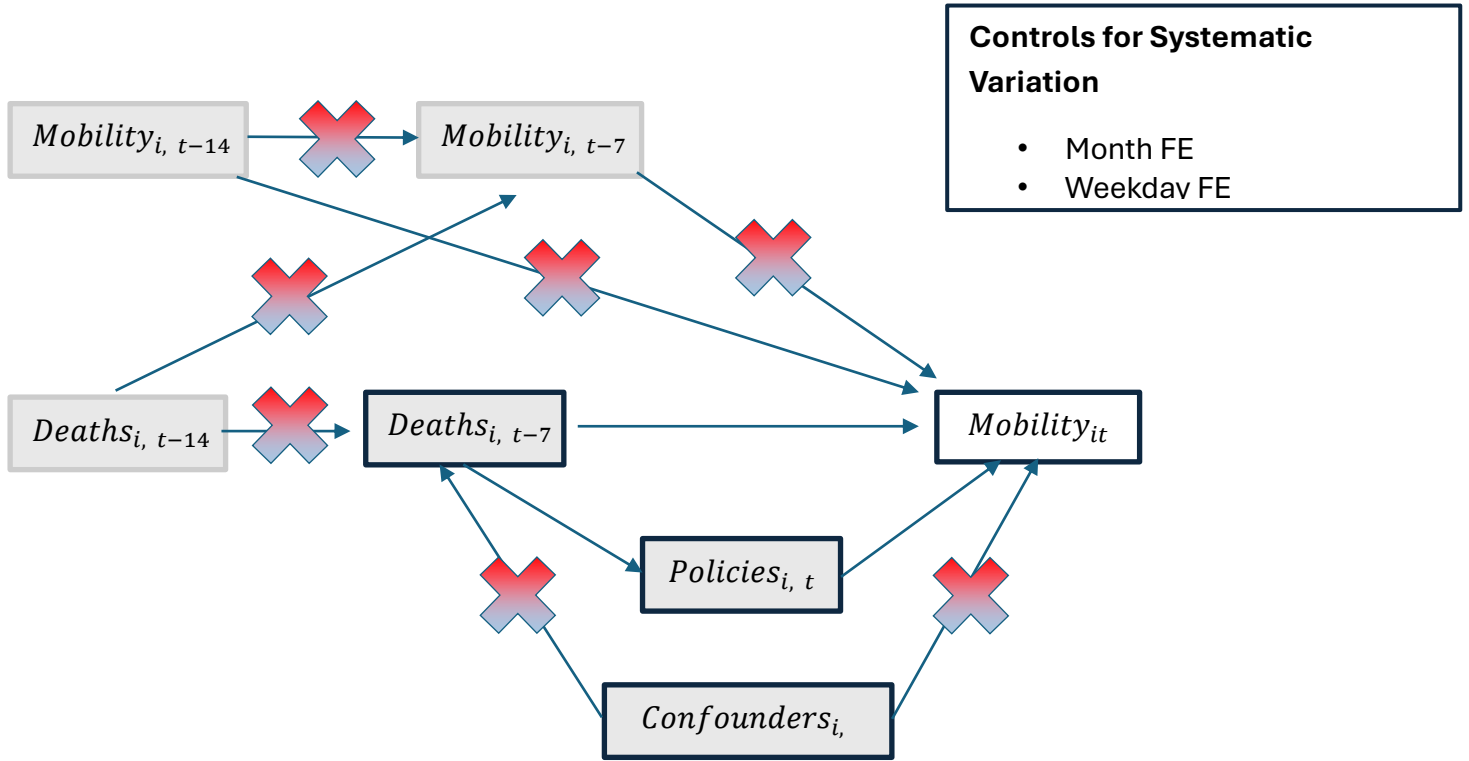
To formally examine the relationship between risk perception and private preventive behavior, we estimated the following baseline fixed effect regression model (see Figure 1 for a DAG representing the assumed causal relationships and temporal structure)

$$\begin{aligned}
& \text{Log}(\text{Mobility}_{it}) \\
&= \alpha + \beta_1 \times \text{Deaths}_{i, t-7} + \beta_2 \times \text{Mobility}_{i, t-7} + \beta_3 \times \text{Mobility}_{i, t-14} \\
&+ \beta_4 \times \text{Month}_t \\
&+ \beta_5 \times \text{County}_i + \beta_6 \times \text{DayWeek}_t + \beta_7 \times \text{Shelter in Place}_{it} + \beta_8 \times \text{Mask} - \text{Mandate}_{it} + \\
&\varepsilon_{it}
\end{aligned}$$

Our main empirical specification used a log-linear regression model to estimate the relationship between COVID-19 mortality risk perception and mobility behavior. The dependent variable, $\text{Log}(\text{Mobility}_{it})$, represents the log-transformed daily mobility level in county i on day t , normalized by the county population to account for differences in population size across regions. The key independent variable, $\text{Deaths}_{i, t-7}$, measures the number of deaths per 10,000 people in county i lagged by seven days, capturing how mortality information from the past week influences current mobility decisions. We lagged mortality by seven days to align with weekly

reporting cycles, account for delay in death reporting, and approximate the time individuals take to perceive and react to evolving risk information through media and social networks. To account for the persistence of mobility patterns, we include lagged mobility ($Mobility_{i,t-7}, Mobility_{i,t-14}$), which control for short-term mobility inertia and ensure that our estimates capture dynamic adjustments to risk perception rather than residual behavioral trends. We further control for county-fixed effects ($County_i$) to account for time-invariant unobserved heterogeneity across counties and month-fixed effects ($Month_t$) to control for broader seasonal trends in mobility. Day-of-the-week fixed effects ($DayWeek_t$) are included to capture systematic differences in daily movement patterns. Additionally, we included policy variables - $Shelter\ in\ Place_{it}$ and $Mask - Mandate_{it}$ - to isolate the effect of risk perception (proxied by mortality) on private preventive behaviors from reductions in mobility that were directly mandated by government interventions. By controlling for these policies, we ensure that our estimates capture voluntary behavioral responses to risk perception rather than government-imposed restrictions on mobility. The coefficient on the lagged death variable represents the growth rate in mobility for every additional death in the last seven days. Finally, we cluster standard errors at the county.

Figure 1. Directed Acyclic Graph (DAG) of the Empirical Identification Strategy



As robustness checks, we implemented three alternative specifications to assess potential model dependence in our main analysis of total mobility during the risk compensation period: (1) we added a 21-day lag of mobility to account for longer-run behavioral persistence; (2) we included a 14-day lag of mortality to account for temporal correlation in deaths and test for sensitivity to longer risk signal windows; and (3) we removed lagged mobility to test whether the estimated effects were driven by serial correlation rather than responses to mortality signals.

Heterogeneity, Temporal Dynamics, and Policy Effects

Mobility across Retail & Recreation, Grocery & Pharmacy, Workplaces, Transit Stations, Parks, and Residential may reflect different types of private preventive behaviors. To capture these distinctions, we separately examined them, each serving as an individual outcome variable in

separate regressions. Retail & Recreation mobility reflects non-essential activities and captures individuals' willingness to visit leisure-related locations despite potential exposure risks. Grocery & Pharmacy mobility represents essential movement, where individuals must balance necessary outings with risk avoidance. Transit Station mobility involves movement with limited capacity for social distancing, yet it remains an essential form of transportation for many. Park mobility differs from the others, as outdoor spaces were widely perceived as safer environments, often serving as a behavioral substitution for riskier indoor activities rather than direct risk avoidance. Residential mobility, measured as time spent at home, is a direct proxy for the extent individuals engage in complete risk avoidance by minimizing exposure to public spaces. All mobility measures are log-transformed and normalized by county population to account for differences in scale across counties. Next, we investigate whether the sensitivity of mobility behavior to risk perception weakens as the pandemic progresses by interacting with time our key independent variable, lagged deaths per 10,000. This effect, often called risk normalization, could also reflect pandemic fatigue. If the impact of mortality on mobility declines over time, it would suggest that initial behavioral responses to perceived risk were strong but diminished as individuals adjusted to prolonged exposure to the pandemic environment.

Finally, we examined how public health policies mediate behavioral responses to risk perception by introducing interaction terms between lagged deaths and policy variables. We first interacted lagged deaths with shelter-in-place orders and then in a separate regression with mask mandates, and finally include a triple interaction between both policies to analyze their combined effect. These interactions allow us to determine whether public policies amplify, dampen, or have no effect on voluntary behavioral responses to risk perception. If the estimated interaction terms are negative, it would suggest that the presence of formal restrictions reinforces mobility reductions

beyond what is driven by risk perception alone. Conversely, if the interaction effects are positive or insignificant, it would indicate that individuals primarily rely on their assessment of risk rather than government-imposed policies when adjusting mobility behaviors.

In all these additional regressions, we maintained the same set of controls, county and time-fixed effects, and clustered standard errors as in our main specification to ensure the robustness of our results. This expanded empirical strategy provides a more nuanced understanding of how individuals adjust private preventive behaviors in response to risk perception, how these responses evolve, and how they interact with public policy measures.

2.6 Results

Our sample includes 1,206 counties and 1,161,394 observations. Over the entire study period, we found that a rise in observed mortality risk (measured as one additional death per 10,000 population, lagged by 7 days) is associated with a 7.9% reduction in mobility ($p < 0.001$),¹ indicating that individuals adjusted their behavior in response to these signals—reflecting an increased demand for private preventive measures. However, this average effect conceals important differences across pandemic stages, each reflecting distinct levels of uncertainty, perceived threat, and behavioral adaptation. During the early pandemic period, the estimated coefficient on observed mortality risk is -0.174 ($p < 0.001$), implying a 15.97% rate of reduction in mobility. This large response likely reflects early panic and heightened uncertainty, when knowledge about the virus was limited and fear was widespread. In the risk compensation period, the behavioral response remains strong but moderates to -0.102 ($p < 0.001$), corresponding to a 9.7% reduction in mobility. This more measured response aligns with the emergence of private

¹ For all log-linear regression results, when indicated we report exact percentage changes using the transformation $(e^{\beta} - 1) \times 100$, where β is estimated coefficient. This conversion provides an accurate interpretation of the effect size in percentage terms.

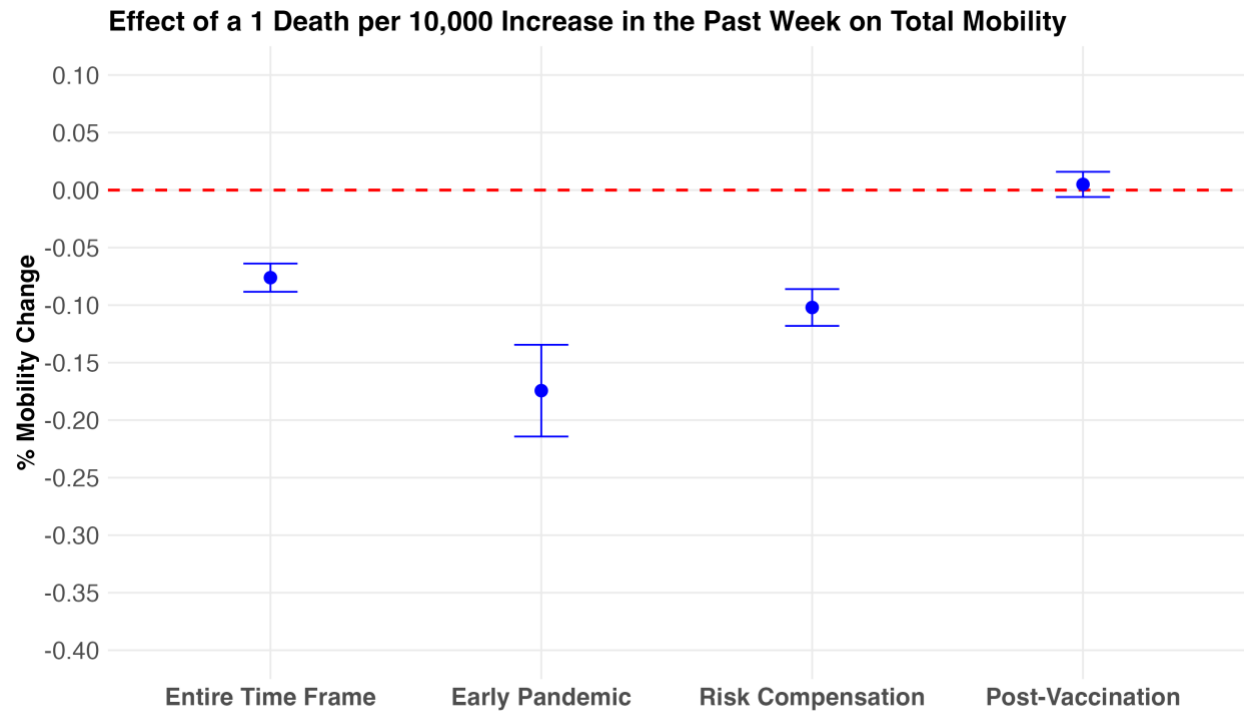
preventive behavior grounded in updated risk perception. Finally, in the post-vaccination period, we found no statistically significant effect of observed mortality risk on mobility, consistent with diminished behavioral sensitivity as perceived safety increased due to population immunity (Table 1 and Figure 2).

Table 1. Effect of Risk Perception and Public Health Policies on Total Mobility Across Pandemic Phases:

Main regression results across defined stages of the pandemic. Outcome: total mobility.

	Entire Time Frame	Early Pandemic	Risk Compensation	Post-Vaccination
Deaths per 10,000 (7-day lag)	-0.076 (CI: -0.088, -0.064) p < 0.001	-0.174 (CI: -0.214, -0.134) p < 0.001	-0.102 (CI: -0.118, -0.086) p < 0.001	0.005 (CI: -0.006, 0.016) p = 0.377
Shelter-in-Place Active	-0.051 (CI: -0.055, -0.046) p < 0.001	-0.092 (CI: -0.099, -0.085) p < 0.001	-0.026 (CI: -0.029, -0.022) p < 0.001	—
Mask Mandate Active	0.001 (CI: -0.000, 0.003) p = 0.154	-0.013 (CI: -0.026, -0.000) p = 0.042	-0.002 (CI: -0.004, 0.000) p = 0.089	-0.002 (CI: -0.005, 0.001) p = 0.166
County FE	✓	✓	✓	✓
Time FE (Month, Day-of-week)	✓	✓	✓	✓
Lagged Mobility Controls	✓	✓	✓	✓

Figure 2. Effect of Risk Perception on Total Mobility Across Pandemic Phases

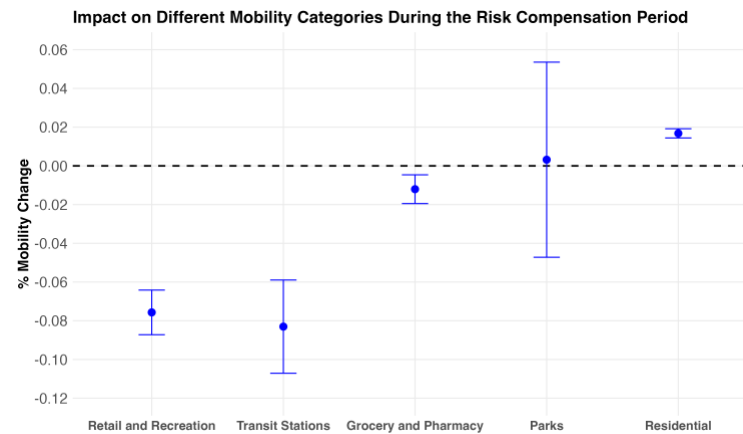


To further unpack these dynamics, we examined how observed mortality risk influenced different types of mobility during the risk compensation period. As different forms of mobility reflect distinct private preventive behaviors, these disaggregated outcomes provide deeper insight into how individuals adjusted their routines in response to perceived risk. We found that higher mortality risk led to significant reductions in Retail & Recreation (-7.32% , $p < 0.001$) and Transit Station (-7.97% , $p < 0.001$) mobility—settings typically associated with discretionary and high-contact activities. These categories show the strongest behavioral adjustments, likely reflecting efforts to limit exposure in non-essential and crowded environments. Workplace mobility also declined substantially (-8.70% , $p < 0.001$), suggesting that even work-related activities were scaled back as risk increased, possibly due to expanded remote work or voluntary avoidance of shared indoor spaces. Grocery & Pharmacy mobility decreased only modestly (-1.19% , $p = 0.001$), likely due to the essential nature of these trips and limited flexibility to substitute them. Parks mobility, however, remained unchanged (0.3% , $p = 0.901$). This null effect is both intuitive and meaningful: outdoor spaces were broadly perceived as lower-risk environments during the pandemic. Our results capture this behavioral distinction, highlighting that individuals did not reduce park visits in response to rising mortality risk. Finally, residential mobility increased by 1.71% ($p < 0.001$), reflecting a shift toward time spent at home, which can be interpreted as a form of private preventive measure (Table 2 and Figure 3).

Table 2. Category-Specific Behavioral Responses to Risk Perception During the Risk Compensation Period:
Regression results for each mobility category as outcome. Period: Risk Compensation.

	Retail & Recreation	Transit Stations	Workplaces	Grocery & Pharmacy	Residential	Parks
Deaths per 10,000 (7-day lag)	-0.076 (CI: -0.087, -0.064) p < 0.001	-0.083 (CI: -0.107, -0.059) p < 0.001	-0.091 (CI: -0.101, -0.080) p < 0.001	-0.012 (CI: -0.019, -0.005) p = 0.001	0.017 (CI: 0.014, 0.019) p < 0.001	0.003 (CI: -0.047, 0.054) p = 0.901
Shelter-in-Place Active	-0.038 (CI: -0.043, -0.034) p < 0.001	-0.023 (CI: -0.032, -0.015) p < 0.001	-0.032 (CI: -0.035, -0.029) p < 0.001	-0.007 (CI: -0.010, -0.005) p < 0.001	0.004 (CI: 0.004, 0.005) p < 0.001	-0.013 (CI: -0.024, -0.002) p = 0.022
Mask Mandate Active	-0.010 (CI: -0.013, -0.006) p < 0.001	-0.003 (CI: -0.010, 0.004) p = 0.375	0.003 (CI: 0.001, 0.005) p = 0.010	-0.007 (CI: -0.009, -0.005) p < 0.001	0.002 (CI: 0.001, 0.002) p < 0.001	-0.011 (CI: -0.022, -0.001) p = 0.036
County FE	✓	✓	✓	✓	✓	✓
Time FE (Month, Day-of-week)	✓	✓	✓	✓	✓	✓
Lagged Mobility Controls	✓	✓	✓	✓	✓	✓

Figure 3. Category-Specific Behavioral Responses to Risk Perception During the Risk Compensation Period



Finally, We examined whether behavioral responses to observed mortality risk varied over time and across policy environments. In the first specification, we found that the effect of observed mortality risk on mobility weakens over time, with the interaction term indicating a 1.0 percentage point attenuation per additional month ($p < 0.001$) (Table 3). This result is consistent with a process of risk normalization or pandemic fatigue^{17–19}.

Turning to policy moderation, we observe that the behavioral response becomes stronger when shelter-in-place orders are active. Specifically, the interaction term suggests an additional 8.65% reduction in mobility in response to observed mortality risk during periods with active shelter-in-place policies ($p < 0.001$). Similarly, mask mandates amplify the effect of observed mortality risk, with an additional 4.29% reduction in mobility ($p = 0.012$). These findings suggest that formal policy interventions may reinforce individual risk perception, prompting a stronger private preventive action. Finally, the triple interaction between observed mortality risk, shelter-in-place, and mask mandates yields a small and statistically insignificant effect of 0.8% ($p = 0.829$), indicating no evidence of a synergistic effect beyond the individual policy interactions (Table 3).

The results remained robust across all alternative specifications conducted during the risk compensation period, where the main estimated effect of observed mortality on total mobility is -0.10 ($p < 0.001$). Including a 21-day lag of mobility yields a slightly attenuated effect of -0.09 ($p < 0.001$), while adding a 14-day mortality lag produces a coefficient of -0.07 ($p < 0.001$), consistent with temporally correlated risk perception. Removing lagged mobility amplifies the effect to -0.14 ($p < 0.001$), suggesting that the main estimate is conservative and not driven by behavioral persistence.

Table 3. Interaction Effects: Temporal Dynamics and Policy Moderation of Risk Responses -

Models testing whether behavioral responses to deaths vary by time and policy environment. Period: Risk Compensation.

Model Specification	Deaths (T-7)	Month FE	Shelter-in-Place	Mask Mandate	Interaction Term(s)
(1) Temporal Dynamics	-0.186 (p<0.0001)	-0.003 (p<0.0001)	—	—	Deaths × Time: 0.010 (p<0.0001)
(2) Interaction with Shelter	-0.093 (p<0.0001)	—	-0.022 (p<0.0001)	—	Deaths × Shelter: -0.083 (p<0.0001)
(3) Interaction with Mask	-0.086 (p<0.0001)	—	—	0.001 (p=0.689)	Deaths × Mask: -0.042 (p=0.012)
(4) Triple Interaction	-0.078 (p<0.0001)	—	-0.022 (p<0.0001)	0.000 (p=0.750)	Deaths × Shelter: -0.082 (p<0.0001), Deaths × Mask: -0.041 (p=0.024), Deaths × Shelter × Mask: 0.008 (p=0.829)

2.7 Discussion

Our contribution makes clear that private behavior is not passive—it is endogenously reactive to perceived health risk and evolves as the informational and epidemiological landscape shifts. We show that individuals don't simply increase the demand for private preventive behaviors in the abstract; rather, they recalibrate specific behaviors based on how they perceive risk exposure and necessity, with observed mortality serving as a signal that shapes those perceptions. Importantly, our disaggregated analysis across different types of mobility domains—ranging from discretionary (e.g., Retail & Recreation) to essential (e.g., Grocery) to substitutive (e.g., Parks)—reveals how different categories of preventive action respond to risk in distinct ways. This heterogeneity uncovers the behavioral logic behind risk-avoidant actions, showing that individuals selectively adjusted their routines in response to evolving local mortality signals.

Equally important, this study shows that public health policies do not merely impose restrictions but also shape private behavior by modulating the strength of voluntary responses. Rather than crowding out risk-avoidant behavior, mandates such as shelter-in-place orders and mask requirements amplify it—suggesting that these policies serve not just as constraints but as catalysts for heightened vigilance. These findings demonstrate that top-down interventions reinforce, rather than replace, private protective behaviors—establishing a mutually reinforcing relationship between institutional mandates and individual action. While prior studies have focused on estimating the average effects of mandates on mobility or behavior (e.g., ^{12,13,20,21}), our analysis revealed a more dynamic interaction as it suggests that mandates not only act as external restrictions that limit movement or prescribe actions but as contextual amplifiers of perceived risk. While Goolsbee and Syverson (2021) highlight the primacy of voluntary behavior and Chernozhukov et al. (2021) decompose average policy effects through behavioral channels,

our analysis goes further by modeling how public health mandates amplify individuals' responsiveness to perceived mortality risk. Moreover, while prior studies focus exclusively on the early months of the pandemic, we analyzed behavioral dynamics across multiple pandemic stages—capturing how responsiveness evolved as the informational and epidemiological context shifted.

In parallel, instead of studying risk compensation behaviors that occur after protection is adopted, we examined how individuals proactively adjust preventive behaviors in response to real-time, objective risk signals. This provides a distinct perspective on behavioral adaptation, in contrast to most of the existing literature in risk compensation behavior, which focuses on reduced vigilance or risk-taking. For instance, behavioral offsets following PrEP initiation or HIV treatment (e.g., ^{5–8}), or after vaccination or mask mandates during COVID-19 (e.g., ^{9–11,22,23}). Rather than assuming behavior changes only once protection is secured, we show that individuals dynamically respond to fluctuations in perceived threat—adjusting their routines in anticipation of risk, not just in reaction to intervention (^{13,24}).

Finally, we introduce a novel methodological framework that integrates SafeGraph's absolute mobility data with Google's category-specific trends to reconstruct daily, domain-specific levels of private movement. Prior studies using mobility data typically rely on relative changes to pre-pandemic baselines (Google Mobility data) or absolute-level data without information on mobility across different categories (e.g., ^{11–13,25,26}). In contrast, our fusion of data sources allows us to recover the absolute level of mobility across six distinct behavioral domains—enabling a more behaviorally grounded analysis of how different types of private preventive actions evolve in response to perceived risk. Using this enriched dataset, we also empirically estimate pandemic fatigue as a declining responsiveness of mobility to mortality-driven risk perception. While the

notion of behavioral fatigue has been theorized and estimated (e.g., ^{27–30}), our analysis provides a direct empirical estimate of the attenuation effect: we found a measurable weakening in behavioral responsiveness—roughly a 1 percentage point decline in mobility elasticity per month—highlighting the erosion of behavioral vigilance over prolonged exposure to risk and the need for adaptive policy strategies to sustain engagement.

While our study provides novel insight into the dynamics of risk-responsive behavior, several limitations warrant acknowledgment. First, despite controlling for observable factors, unmeasured influences—such as local media, political attitudes, or institutional trust—may also shape both behavior and its responsiveness to risk. In addition to actual mortality, perceived risk may be shaped by subjective interpretations and by how different populations internalize mortality information, leading to variation in behavioral responses. Second, while mobility is a valuable proxy for preventive action, it does not capture other protective behaviors like mask-wearing or physical distancing within locations. Third, our county-level analysis reflects aggregate patterns and cannot account for individual-level heterogeneity or motivations. These limitations notwithstanding, our findings offer important macro-level evidence on how private behavior and public policy interact in dynamic and mutually reinforcing ways.

Chapter 3: ENDOGENIZING RISK COMPENSATION IN EPIDEMIC MODELING: AN ECONOMIC-SEIRDS

3.1 Abstract

Background

Traditional compartmental models of infectious disease transmission often overlook how individuals dynamically adjust their behavior in response to perceived risk. Endogenous behavioral feedback—particularly risk compensation in response to rising or falling epidemic severity—can profoundly shape outbreak dynamics but is rarely incorporated in mechanistic models.

Methods

We developed the *Economic-SEIRDS model*, a delay differential extension of the standard SEIRDS framework that introduces endogenous behavioral feedback via a mortality-responsive contact rate. Individuals reduce contacts in response to recent observed mortality, generating a feedback loop where behavior and transmission co-evolve. To reflect real-world lags in behavioral adaptation, the model incorporates delays in how mortality affects behavior. The strength of this behavioral response is governed by an empirically estimated parameter reflecting responsiveness to local mortality risk. An extension allows this responsiveness to wane over time, capturing pandemic fatigue.

Results

Mortality-responsive feedback delays the infection peak, reduces its magnitude, and generates oscillatory wave patterns—producing multiple waves rather than a single explosive outbreak. The traditional model overestimates the first peak and fails to capture recurring waves, underestimating the persistence of transmission. These differences arise from time-varying

contact rates in the Economic-SEIRDS model, which decline with rising mortality and rebound as perceived risk subsides. Sensitivity analyses showed that stronger behavioral responsiveness yields smaller, more staggered peaks, lowering total burden but prolonging the epidemic. A qualitative validation shows the model more closely mirrors observed U.S. COVID-19 mortality patterns than standard SEIRDS models. Pandemic fatigue showed that as responsiveness to mortality weakens over time, contact rates rebound, eroding behavioral control and sustaining transmission.

Conclusions

By endogenizing behavior in response to mortality risk, the Economic-SEIRDS model captures the adaptive interplay between individual behavior and disease dynamics. This endogenous co-evolution of behavior and epidemic severity creates a self-regulating system in which private action dynamically responds to real-time risk signals. This approach offers a tractable, flexible framework that improves epidemic realism and supports more effective public health modeling and policy design.

3.2 Introduction

Infectious disease dynamics are shaped not only by biological transmission processes but significantly by adaptive human behaviors driven by risk perception. Empirical and theoretical evidence consistently demonstrates that individuals voluntarily adjust their behaviors—engaging in risk compensation behaviors—to mitigate infection risks.^{31,32} Such adjustments, termed private preventive measures, include actions like reducing mobility, avoiding public interactions, or adopting protective measures in response to perceived disease threats. These voluntary behavioral changes create dynamic feedback loops between disease spread and preventive actions undertaken by individuals. Critically, the presence and strength of these feedback loops

can determine whether an outbreak becomes self-limiting or escalates into sustained epidemic waves, depending on the preventive behaviors incentivized. For example, heightened risk perception prompts intensified private preventive measures, thus suppressing transmission. Conversely, successful mitigation of disease spread can lower risk perception, leading to behavioral relaxation and potentially triggering renewed transmission.^{31,33,34}

Traditional compartmental epidemiological models, however, commonly assume static or exogenously determined behaviors, typically fixing contact rates or imposing externally determined scenarios.^{35,36} Such simplifications overlook the complexity of endogenous human behavior as individuals navigate intricate behavioral trade-offs between safeguarding personal and public health and engaging in activities that maximize personal utility or well-being.³⁷ Ignoring this endogenous feedback loop can lead to several unintended consequences in public health policy. Notably, models may inaccurately estimate the effectiveness of interventions, either by overestimating their sustained impact—assuming preventive behaviors remain unchanged—or by underestimating effects due to oversimplified assumptions of uniform responses across diverse populations. Consequently, policies such as information campaigns, vaccination subsidies, and targeted testing programs may yield unintended and counterproductive outcomes.^{38,39}

Explicitly acknowledging and integrating risk compensation behaviors into epidemiological modeling is therefore critical for accurately capturing infectious disease dynamics and designing effective public health interventions. First, failing to account for behavioral feedback loops during infectious disease outbreaks can lead to unintended consequences. Declining perceived risk—often following initial successes of preventive measures—can prompt individuals to

reduce adherence to private preventive behaviors, inadvertently fueling disease resurgence. This underscores the necessity of incorporating the evolving interplay between risk perception and private preventive actions into epidemiological frameworks. Second, ignoring risk compensation behaviors complicates the accurate evaluation of preventive or therapeutic interventions.^{40–42} The introduction of new interventions—such as vaccines or prophylactic treatments—often shifts individual risk perceptions significantly. As perceptions adjust, individuals alter their preventive behaviors in ways not originally anticipated, potentially undermining the intended benefits of these interventions. Therefore, rigorous evaluation of interventions requires explicitly modeling how individual risk perceptions and preventive behaviors dynamically evolve with changing disease landscapes.

Despite empirical evidence linking risk perception directly to the demand for private preventive measures, existing epidemiological models typically continue to treat these behaviors as static or externally defined.⁴³ While some theoretical studies attempt to incorporate behavioral feedback loops through simulations, these efforts frequently lack tend to emphasize aggregate societal outcomes rather than explicitly modeling individual-level risk compensation behaviors.⁴⁴

This study directly addresses this critical gap by empirically integrating risk compensation behaviors into a mechanistic epidemiological framework. Specifically, we leverage empirically estimated relationships between risk perception—proxied through local mortality signals—and changes in private preventive measures, particularly mobility reductions. By embedding these empirically grounded behavioral responses into a delay-differential SEIRDS transmission model,

we adapted and transformed it into an Economic- SEIRDS model that explicitly endogenizes individual behavior. Our framework contributes to existing modeling practice in three essential ways: first, by empirically grounding behavioral parameters; second, by explicitly incorporating behavioral response delays; and third, by systematically examining how these endogenous behavioral feedback loops affect epidemic trajectories, clarifying conditions under which outbreaks become self-limiting or escalate.

Although our approach is broadly applicable to infectious diseases characterized by dynamic risk environments, we specifically implement and qualitatively validate our model in the context of COVID-19, leveraging detailed empirical estimates of risk perception and mobility-based preventive behaviors.

3.3 Methods

Behavioral Feedback and Risk Compensation

A defining feature of the Economic-SEIRDS model is its incorporation of behavioral feedback, whereby individuals endogenously adjust their private preventive measures (e.g., reduced mobility, social distancing) in response to mortality-driven risk perception. In our analysis, behavioral change is modeled as a function of observed mortality—a proxy for objective epidemic severity—but we assume this effect is mediated through individual perception of risk, which is itself unobserved. This adjustment embodies the economic principle of risk compensation: as perceived risk rises, individuals intensify preventive actions; as it falls, they relax them. Such dynamic behavior creates feedback loops between epidemic outcomes and transmission rates that are absent in standard compartmental models.

Perceived risk is proxied by recent observed mortality, a signal that is psychologically salient, socially influential, and widely disseminated. Prior research supports the use of local mortality as

a behaviorally relevant risk signal: compared to case counts, deaths are more visible, more emotionally resonant, and less susceptible to testing and reporting biases (e.g., Montano-Campos et al, 2025). Individuals form beliefs about disease severity by observing how many people in their communities have recently died, adjusting their behavior accordingly. In our framework, individuals respond to mortality observed one week earlier, denoted $D(t - 7)$, measured in deaths per 10,000 population. The behavioral responsiveness of mortality-driven risk perception is captured by the parameter θ , which quantifies the percentage change in the contact rate (i.e., the inverse demand for private preventive measures) in response to a one-unit increase in lagged mortality. The behavioral responsiveness of mortality-driven risk perception is captured by the parameter θ , which quantifies the percentage change in the contact rate (i.e., the inverse demand for private preventive measures) in response to a one-unit increase in lagged mortality. This behavioral parameter, θ , governs the strength of the endogenous feedback loop between epidemic severity and behavioral adaptation. It determines whether the system exhibits self-limiting dynamics—where rising mortality leads to reduced transmission through behavioral contraction—or whether declining mortality leads individuals to relax preventive behaviors, increasing contact rates and thereby enabling renewed transmission and potential epidemic resurgence.² To formalize this relationship, we defined the effective contact rate as

$$c^{eff}(t) = c_0 \times \exp [\theta \times D(t - 7)]$$

Where:

- c_0 : is the baseline contact rate with no private prevention engagement.

² This behavioral feedback mechanism distinguishes the Economic-SEIRDS model from the traditional SEIRDS framework, where contact rates are assumed fixed and unresponsive to epidemic dynamics (see Section 2.2).

- $D(t - 7)$: is the number of disease-induced deaths per 10 000 population observed seven days earlier.
- θ : is the behavioral responsiveness parameter, governing the elasticity of contact behavior with respect to mortality driven risk perception.

We allow $c_{eff}(t)$ to vary multiplicatively with perceived risk. This functional form captures the idea that contact rates decline exponentially as mortality-driven risk perception increases and the effect is governed by θ . The specification is flexible, allowing for a wide range of behavioral responses: when $\theta < 0$, even small increases in recent mortality can lead to sharp reductions in contact rates and when $\theta = 0$, behavior is fixed, replicating the traditional SERIDS model.

Importantly, the behavioral function relies on lagged outputs of the epidemic model itself—specifically, recent deaths—to determine $c_{eff}(t)$. This introduces a dynamic feedback loop in which a model output becomes a model input. Standard ordinary differential equation (ODE) systems are not equipped to handle such temporal dependencies, where the state at time t depends on a window of past outcomes. To capture this structure formally, we adopted a delay differential equation (DDE) approach, allowing mortality in a previous time interval to influence current transmission.

By incorporating a mortality-driven behavioral response in this manner, the model captures rich dynamics—such as delayed epidemic peaks, dampened transmission, and oscillatory behavior—that emerge when individual behavior is allowed to co-evolve with epidemic risk. In the following section, we describe how this feedback mechanism is embedded within a SEIRDS transmission framework.

Economic-SEIRDS Model Structure

To evaluate how endogenous behavioral responses shape epidemic dynamics, we extend the traditional SEIRDS framework to include both behavioral feedback and disease-induced mortality. Our resulting model, which we refer to as the Economic-SEIRDS model, consists of five compartments: Susceptible (S), Exposed (E), Infectious (I), Recovered (R), and Deceased (D). We also incorporate waning immunity, allowing recovered individuals to return to the susceptible pool. Individuals transition between compartments according to biological processes and behaviorally mediated transmission dynamics.

The total population is denoted by $N(t)$, assumed to remain constant over time through equal birth and natural death rates μ . The rate of new infections is determined by a behaviorally responsive contact rate, which adjusts endogenously based on lagged mortality-driven risk perception (see Section 2.1).

The model is governed by the following delay differential equations:

$$\frac{dS}{dt} = \mu N(t) + \omega R(t) - S(t) \times c^{eff}(D_{t-7}) \times I(t) \times \rho - \mu S(t)$$

$$\frac{dE}{dt} = S(t) \times c^{eff}(D_{t-7}) \times I(t) \times \rho - \sigma E(t) - \mu E(t)$$

$$\frac{dI}{dt} = \sigma E(t) - \gamma I(t) - \delta I(t) - \mu I(t)$$

$$\frac{dR}{dt} = \gamma I(t) - \omega R(t) - \mu R(t)$$

$$\frac{dD}{dt} = \delta I(t)$$

Where:

- $c^{eff}(t) = c_0 \times \exp [\theta \times D(t - 7)]$ is the behaviorally adjusted contact rate
- ρ is the probability of transmission per contact between a susceptible and infectious individual,
- σ is the transition rate from exposed to infectious (inverse of the incubation period),
- γ is the recovery rate,
- δ is the disease-induced mortality rate,
- ω is the rate of immunity waning, and
- μ is the natural birth and death rate.
- θ is the behavioral responsiveness parameter, governing the elasticity of contact behavior with respect to mortality driven risk perception.

Because the behavioral function depends on lagged mortality, the system cannot be expressed using standard ordinary differential equations. We therefore adopted a delay differential equation (DDE) framework to formally capture the temporal structure introduced by behaviorally responsive contact rates. This modeling approach is not only mathematically appropriate—it also reflects the real-world behavioral feedback loop in which individuals observe changes in disease severity (e.g., rising deaths), internalize perceived risk, and adjust their preventive behaviors only after a delay.

When the behavioral responsiveness parameter θ is set to zero, the Economic-SEIRDS model collapses to the traditional SEIRDS framework with a fixed contact rate ($c^{eff}(t) = c_0$). In this

special case, individual behavior does not respond to changes in perceived epidemic risk, and transmission dynamics unfold purely based on biological and demographic processes. This correspondence highlights that our model is a direct generalization of the traditional SEIRDS structure, with the traditional formulation fully recoverable when behavioral responsiveness is absent. Under such assumptions, a standard ordinary differential equation system is sufficient to capture the epidemic dynamics, and delay-based modeling is no longer necessary.

Baseline Model Parameters

The behavioral responsiveness parameter ($\theta = -0.186$) was empirically estimated using a fixed-effects panel regression that models US county-level changes in mobility as a function of lagged local COVID-19 mortality (Montano-Campos et al, 2025). Specifically, θ reflects the elasticity of contact reduction in response to perceived epidemic risk. See Appendix A for additional details.

The baseline contact rate ($c_0 = 12.17$) and the transmission probability per contact ($\rho = 0.1073$) were obtained from a calibrated transmission model estimated using data from early 2020, prior to the widespread adoption of non-pharmaceutical. The baseline contact rate is particularly relevant in our setting, as it reflects social mixing levels before the onset of private preventive behavior. The transmission probability reflects the likelihood of infection per contact during the early phase of the outbreak.

Table 4. Parameter Values Used in the Economic-SEIRDS Model

Parameter	Value	Description	Reference
Behavioral Dynamics			
c_0	12.17	Baseline contact rate	⁴⁵
θ	-0.186	Behavioral responsiveness to lagged mortality (elasticity of contact rate)	See Appendix
Epidemiological Parameters			
ρ	0.1073	Probability that a contact leads to infection	⁴⁵
σ	1/5.2	Rate of progression from exposed to infectious (mean incubation: 5.2 days)	⁴⁵
γ	1/7	Recovery rate (mean infectious duration: 7 days)	⁴⁵
δ	0.025	Daily disease-induced mortality rate among infectious individuals	Calibrated to amplify behavioral feedback; consistent with upper-bound mortality estimates in prior models (e.g., add the papers in the comments/notes) ⁴⁵⁻⁵⁰
ω	1/120	Rate of waning immunity (average immunity duration: 120 days)	⁵¹
Demographic Parameters			
N	500,000	Total population size	Assumption
μ	0.00002 7	Natural birth/death rate	Based on CDC estimate (0.98% annual natural mortality)

All other epidemiological and demographic parameters used in the model are reported in Table 1 and were drawn from standard estimates in the COVID-19 modeling literature.

Qualitative Model Validation

To assess whether the Economic-SEIRDS model produces epidemic dynamics consistent with observed patterns, we conducted a qualitative comparison between simulated daily deaths and real-world COVID-19 mortality data from the United States. While the parameter values described above are used in our main simulation analyses, we slightly adjusted certain inputs—such as transmission probabilities and reinfection dynamics—to reflect the broader epidemiological conditions of 2020–2021, including multiple circulating strains and evolving transmissibility. Although the model remains stylized and is not calibrated to any specific region, we found that incorporating endogenous behavioral feedback produces epidemic curves that more closely mirror real-world dynamics—particularly in terms of dampened peaks, delayed timing, and oscillatory behavior—than the traditional SEIRDS model. This qualitative alignment lends face validity to the core behavioral mechanism embedded in the model. Full details and results are provided in Appendix B.

Sensitivity Analysis: Behavioral Responsiveness Parameter (θ)

To evaluate how the strength of behavioral feedback influences epidemic dynamics, we perform a sensitivity analysis by varying the behavioral responsiveness parameter θ while holding all other model parameters constant. This parameter governs the elasticity of contact behavior with respect to lagged mortality-driven risk perception. We simulated epidemic trajectories under four alternative values of θ : 0 (corresponding to the traditional SEIRDS model with no behavioral adaptation), -0.09 (a dampened feedback response), -0.27 (an intensified feedback response),

and -0.18 (our empirically estimated baseline). This allows us to trace the implications of weaker or stronger behavioral reactions to mortality-driven risk perception.

The analysis proceeds in two parts. First, we simulated the full trajectory of the Economic-SEIRDS model for each θ value, plotting daily new infections and deaths over time. This enables visual inspection of how the magnitude and timing of epidemic waves vary with behavioral responsiveness. Second, to systematically characterize these differences, we extracted and compared the timing and peak values of successive waves of infections and deaths across θ values. These comparisons allowed us to isolate the role of behavioral feedback strength in modulating epidemic scale and temporal structure.

All simulations are performed using the same baseline parameterization described in Section 2.3. The implementation uses delay differential equations to ensure that behavior adjusts based on a seven-day lag in mortality, consistent with our empirical specification.

Modeling Diminishing Behavioral Responsiveness (Pandemic Fatigue)

To explore how waning behavioral vigilance affects epidemic dynamics, we extended the Economic-SEIRDS model to allow for diminishing behavioral responsiveness over time—a phenomenon commonly referred to as pandemic fatigue. In this extended version, the behavioral responsiveness parameter θ gradually weakens, reflecting a reduced tendency to maintain preventive behaviors in response to ongoing mortality risk.

We operationalize this dynamic by allowing θ to increase (i.e., become less negative) by a fixed increment every 30 days, thereby reducing the strength of the behavioral feedback loop over

time. The monthly adjustment factor $\theta = 0.0105$ is drawn from empirical estimates of declining responsiveness to mortality signals (Montano-Campos et al., 2025).

Under this structure, the effective contact rates become:

$$c^{eff}(t) = c_0 \times \exp [\theta(t) \times D(t - 7)]$$

With the time-varying behavioral responsiveness defined as:

$$\theta(t) = \theta_0 + \alpha \times \lfloor \frac{t}{30} \rfloor$$

Where θ_0 is the baseline responsiveness and $\lfloor \frac{t}{30} \rfloor$ denotes the number of full months elapsed (i.e., the floor function applied to time in days divided by 30). This approach ensures a stepwise attenuation of behavioral sensitivity to mortality over the course of the epidemic.

This extended formulation allows us to explore how declining behavioral responsiveness alters disease dynamics. We simulated epidemic trajectories under two scenarios: (1) the baseline Economic-SEIRDS model with constant θ , and (2) a pandemic fatigue scenario in which θ weakens gradually over time. We compared the resulting effective contact rates and epidemic outcomes across these two models to assess how reduced behavioral adherence alters the scale and timing of infections and deaths.

3.4 Results

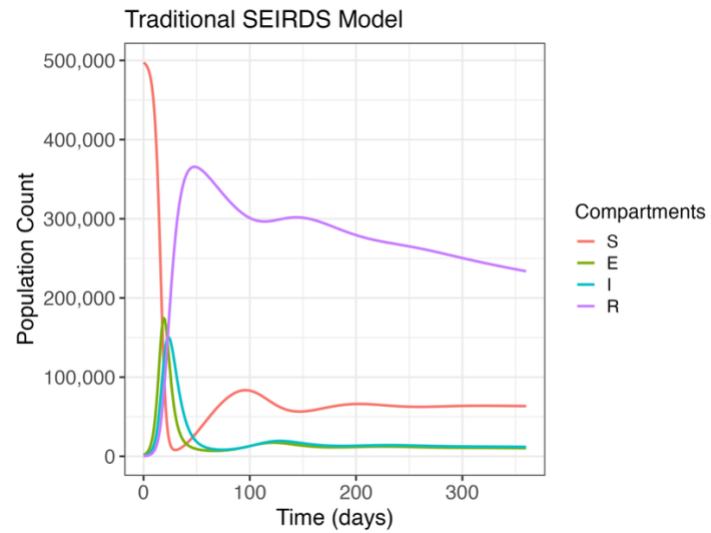
We compared epidemic dynamics under the traditional SEIRDS model—which assumes fixed behavior—with our Economic-SEIRDS framework, which incorporates mortality-responsive behavioral feedback. The differences between the two models are substantial and underscore the importance of endogenizing private preventive behavior.

Figure 4. Epidemic Dynamics With and Without Behavioral Feedback

(a) Traditional SEIRDS model with fixed contact rates (no behavioral feedback).

(b) Economic-SEIRDS model with endogenous contact rates in response to mortality-driven risk perception (7-day lag).

a)



b)

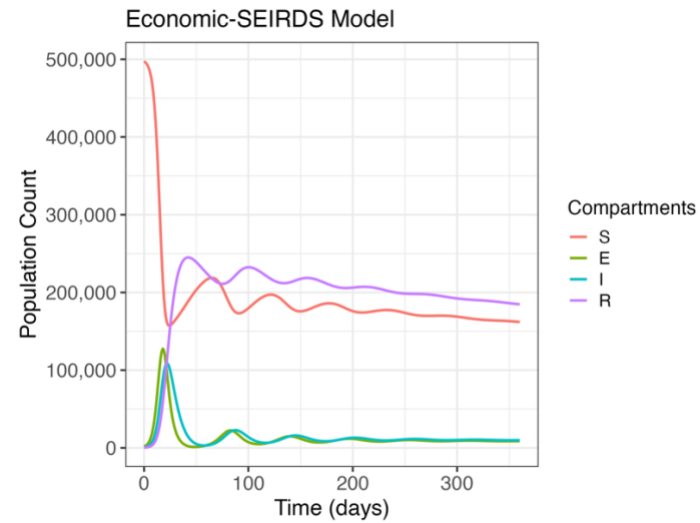
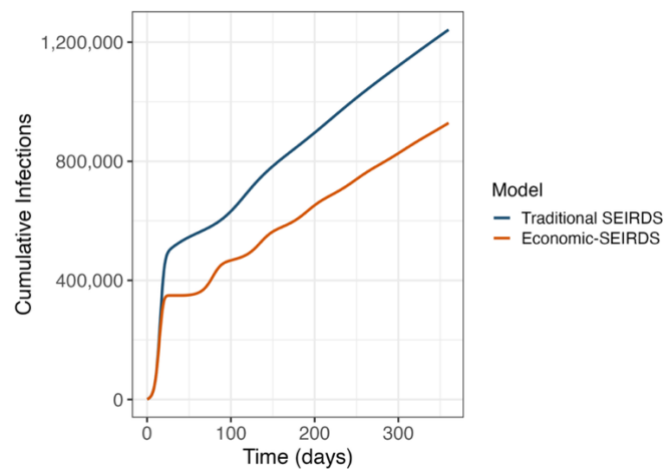
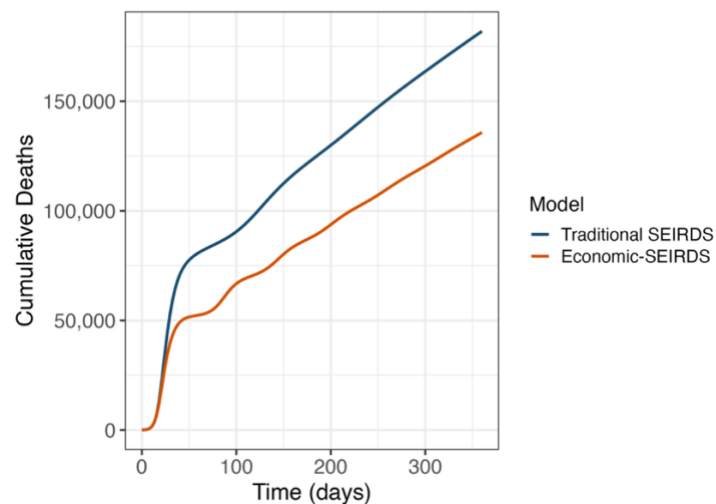


Figure 5. Cumulative Epidemic Outcomes Under Traditional and Economic-SEIRDS Models

(a) Cumulative infections over a 365-day simulation.



(b) Cumulative deaths over a 365-day simulation.

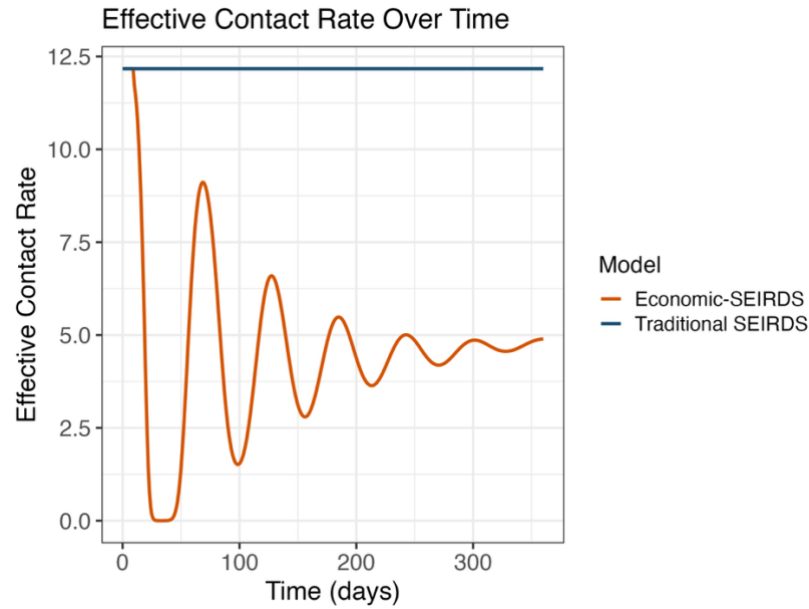


Under the traditional SEIRDS model, the contact rate remains constant over time, resulting in a sharp and early epidemic peak with limited dampening (Figure 4a). This is reflected in the number of individuals in each disease compartment, particularly the rapid rise and fall in the infected population. In contrast, the Economic-SEIRDS model endogenizes behavior, allowing

the contact rate to decline in response to lagged mortality signals. The resulting compartment trajectories show a flatter, delayed infection peak and oscillatory transitions between compartments over time (Figure 4b), driven by feedback between perceived risk and private preventive behavior. Notably, the traditional model yields a more explosive early outbreak and reaches equilibrium more quickly, while the Economic-SEIRDS model produces a more restrained epidemic that remains dynamically unstable for a longer period before stabilizing. These behavioral adjustments also result in markedly different cumulative outcomes. Over the course of a one-year simulation, the Economic-SEIRDS model predicts substantially fewer cumulative infections and deaths than the traditional model (Figure 5). This divergence arises because, in the Economic-SEIRDS model, rising mortality prompts behavioral contraction—lowering contact rates and interrupting transmission chains. In contrast, the traditional model lacks such feedback, allowing infection and mortality to accumulate unchecked. Specifically, the Economic-SEIRDS model results in 313,328 fewer infections and 46,138 fewer deaths after one year.

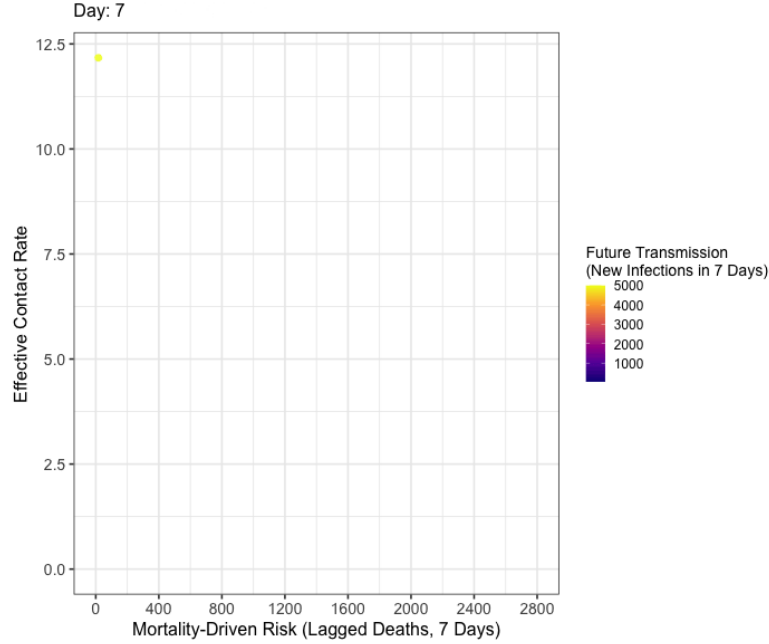
The behavioral mechanism driving these differences is visualized in Figure 6. While the traditional SEIRDS model maintains a constant contact rate, the Economic-SEIRDS model generates a time-varying contact rate that dynamically declines in response to perceived mortality risk. This flexible contact structure captures individuals' adaptive engagement in private preventive measures and is central to the model's ability to attenuate transmission.

Figure 6. Effective Contact Rate in Traditional vs. Economic-SEIRDS Models



These endogenous feedback dynamics are further illustrated in Figure 7, where mortality-driven risk perception triggers cyclical reductions in contact rates that subsequently suppress new infections. The co-evolution of behavior and epidemic severity produces repeating waves—periods of heightened mortality induce behavioral contraction, which lowers transmission, followed by behavioral relaxation as perceived risk declines. This dynamic feedback loop captures the core mechanism of the Economic-SEIRDS model: individuals respond to rising mortality by reducing contact, thereby slowing spread, but gradually resume higher contact rates once risk perceptions fade, allowing transmission to re-emerge.

Figure 7. Behavioral Feedback Loop in the Economic-SEIRDS Model



We next examine how varying the strength of the behavioral response (θ) affects epidemic trajectories. When $\theta = 0$ —corresponding to the traditional SEIRDS model—contact rates are static, and the epidemic unfolds uninhibited. As θ becomes more negative, indicating stronger behavioral responsiveness, infection and death peaks are reduced and delayed, and epidemic waves become more pronounced (Figure 8). These results reflect the self-limiting dynamics introduced by behavioral feedback: stronger responses generate smaller initial peaks but extend the epidemic’s temporal footprint, producing prolonged but more controlled outbreaks (see Appendix B for analogous results under a lower baseline contact rate of $c_0 = 6$).

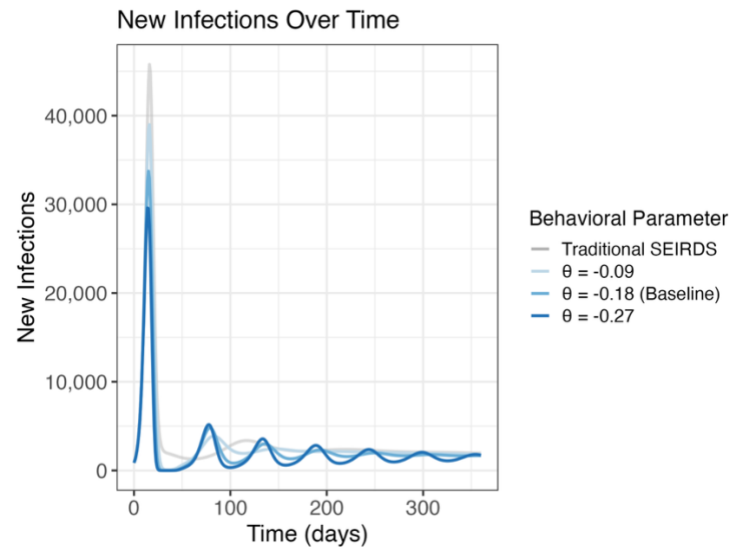
This pattern is further reinforced in Figure 9, which tracks the magnitude and timing of successive death peaks across values of θ . The traditional SEIRDS model overestimates the initial death peak and underestimates subsequent waves, failing to capture the behavioral adaptation that flattens and redistributes transmission over time. In contrast, the Economic-

Figure 8. Sensitivity of Epidemic Outcomes to Behavioral Responsiveness (θ , elasticity of contact behavior to mortality-driven risk perception)

(a) New infections over time under varying behavioral response parameters.

(b) New deaths over time under varying behavioral response parameters.

a)



b)

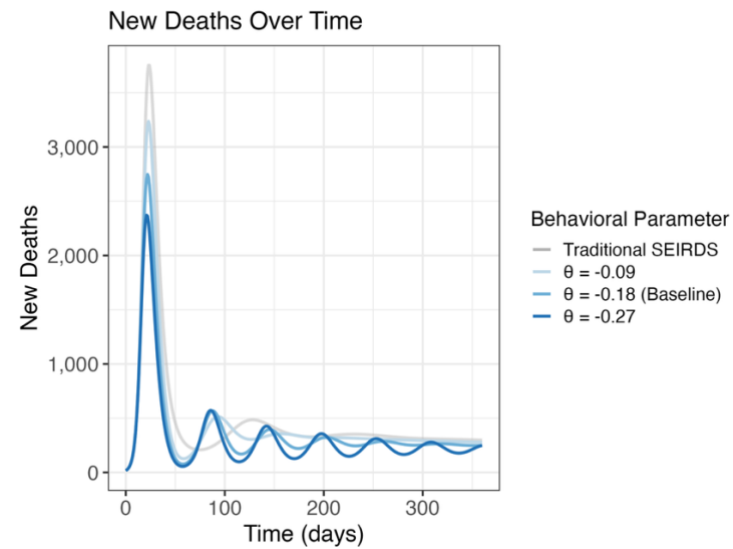
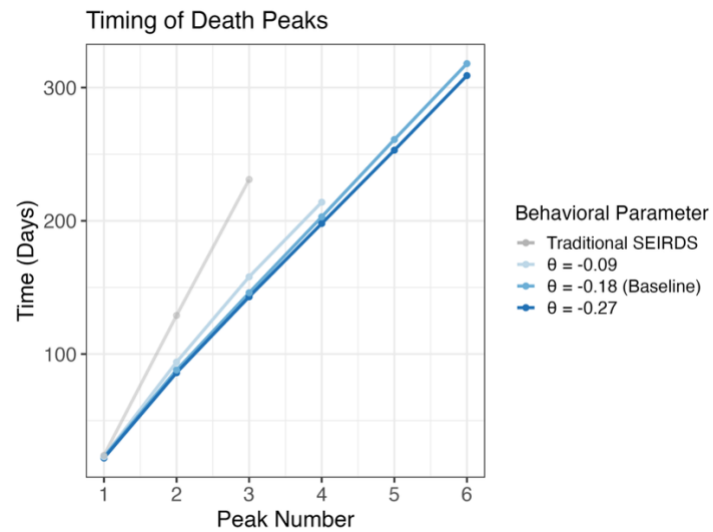


Figure 9. Peak Dynamics Under Varying Levels of Behavioral Responsiveness (θ , elasticity of contact behavior to mortality-driven risk perception)

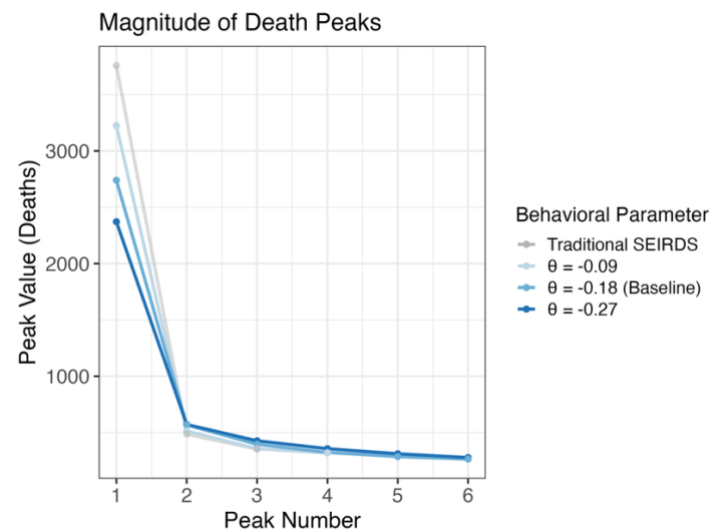
(a) Timing of death peaks across successive epidemic waves.

(b) Magnitude of death peaks across successive epidemic waves.

a)



b)



SEIRDS model—with more negative θ —produces a more balanced sequence of smaller, more frequent peaks. Importantly, stronger behavioral feedback delays the timing of subsequent outbreaks, as preventive measures suppress transmission for longer intervals before relaxation allows resurgence.

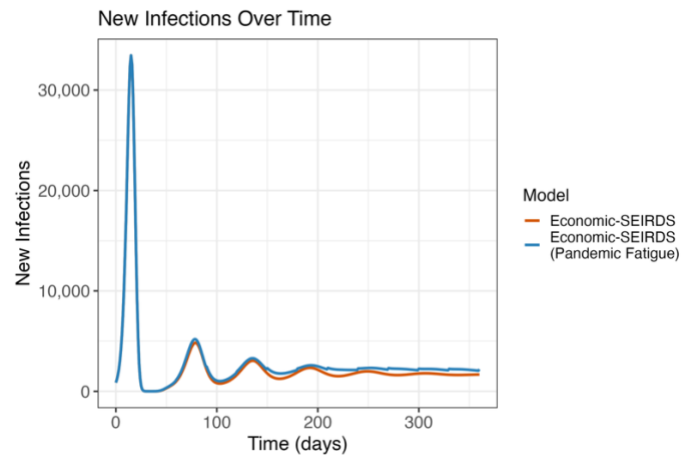
To explore how waning behavioral vigilance affects epidemic dynamics, we extend the Economic-SEIRDS model to incorporate pandemic fatigue, wherein behavioral responsiveness (θ) diminishes gradually over time. Figure 7 shows that the pandemic fatigue scenario yields higher peaks in infections and deaths and sustains elevated levels between waves. While the system still exhibits oscillatory self-limiting behavior, the reduced strength of behavioral responses leads to less effective transmission suppression, resulting in higher overall epidemic burden. These findings highlight the destabilizing effects of pandemic fatigue and the importance of maintaining behavioral responsiveness to control long-term epidemic dynamics.

Finally, Figure 10 compares the time path of the effective contact rate across the baseline Economic-SEIRDS model and the pandemic fatigue variant. In the early epidemic phase, both models exhibit sharp reductions in contact as mortality rises. However, under pandemic fatigue, the contact rate becomes progressively less responsive to ongoing mortality risk and begins to trend upward again. Unlike the model without pandemic fatigue—which converges to a stable lower contact rate—the fatigue model exhibits a rebound in contact behavior, reflecting a dampening of risk-avoidant behaviors and a reversion toward pre-epidemic interaction levels. This weakening of the behavioral feedback loop erodes the self-limiting dynamic of the epidemic, allowing for more persistent transmission.

Figure 10. Impact of Pandemic Fatigue on Epidemic Dynamics (behavioral responsiveness weakens as θ decreases over time in absolute value)

- (a) New infections over time in the Economic-SEIRDS model vs. Economic-SEIRDS with Pandemic Fatigue.*
(b) New deaths over time in the Economic-SEIRDS model vs. Economic-SEIRDS with Pandemic Fatigue.

a)



b)

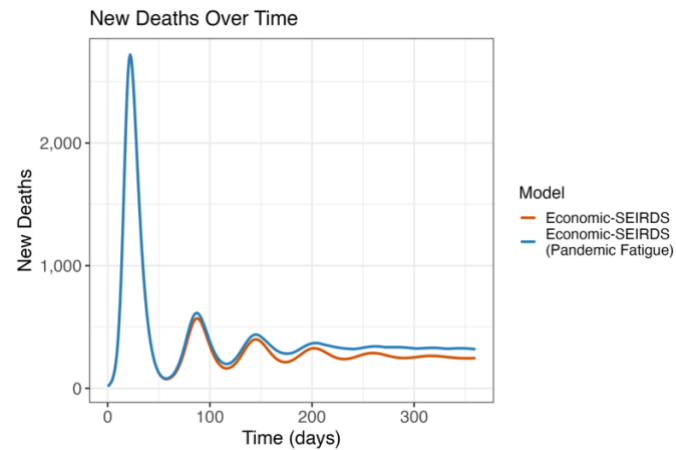
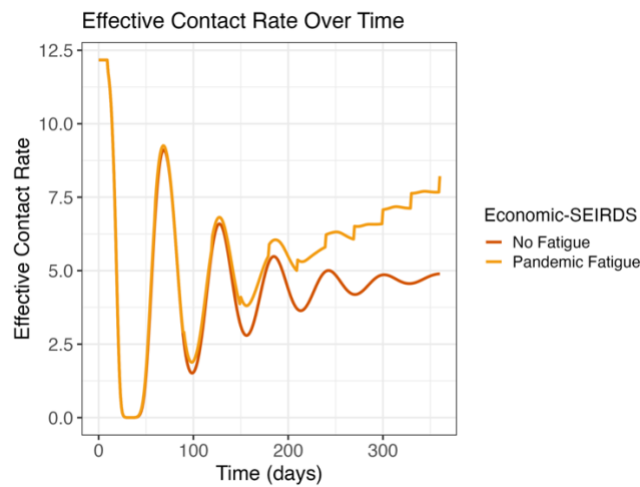


Figure 11. Effective Contact Rate Over Time With and Without Pandemic Fatigue



3.5 Discussion

This study shows that incorporating behavioral feedback loops into epidemic models—where observed mortality influences contact behavior, which in turn shapes transmission and future mortality—fundamentally alters the predicted course of an outbreak. By endogenizing behavior through a mortality-responsive contact rate, our Economic-SEIRDS framework captures the dynamic feedback cycle in which individuals adjust preventive actions in response to objective risk signals. While individual perception of risk is not directly observed, we assume that changes in observed mortality affect behavior via this unmeasured perception channel. Compared to traditional SEIRDS models that treat behavior as fixed, our simulations reveal that incorporating endogenous behavior substantially reshapes epidemic trajectories. Specifically, we found that mortality-responsive feedback delays the infection peak, reduces its magnitude, and generates oscillatory wave patterns—reflecting subsequent waves of transmission—rather than a single explosive outbreak. The traditional model overestimates the size of the first peak while failing to capture recurring waves, underestimating the persistence of transmission over time. The

Economic-SEIRDS model predicts over 300,000 fewer infections and more than 46,000 fewer deaths across a one-year period, highlighting the magnitude of prevention that can arise from dynamic behavioral adaptation.

These differences are driven by time-varying contact rates in the Economic-SEIRDS model, which decline in response to rising mortality and rebound as perceived risk subsides. This behavioral mechanism generates alternating phases of contraction and relaxation in contact behavior, suppressing transmission when deaths are high and allowing resurgence as vigilance fades. Our sensitivity analysis shows that stronger behavioral responsiveness produces smaller and more staggered epidemic peaks, reducing overall burden but extending the epidemic's duration. Finally, our qualitative validation confirms that the Economic-SEIRDS model more closely aligns with real-world mortality patterns during the U.S. COVID-19 epidemic: it reproduces the empirically observed outcome where the second wave of deaths exceeds the first, whereas the traditional model incorrectly predicts the opposite. This alignment lends face validity to the behavioral feedback mechanism and reinforces its relevance for accurately modeling infectious disease dynamics. Incorporating this single mechanism already improves model realism, suggesting that further refinements will only enhance accuracy.

The underlying mechanism driving these dynamics is a recursive feedback loop between mortality risk and private preventive behavior. As mortality rises, individuals perceive greater risk and reduce contact rates, slowing transmission; as mortality falls, perceived risk declines, leading to behavioral relaxation and potential resurgence. This endogenous co-evolution of behavior and epidemic severity creates a self-regulating system in which private action dynamically responds to real-time risk signals. Traditional compartmental models miss this adaptive behavioral component, often treating prevention as fixed or externally imposed, and

therefore mischaracterize both the timing and magnitude of epidemic peaks. By explicitly modeling behavior as a responsive function of epidemic severity, our framework captures the shifting interplay between risk and prevention that defines real-world disease dynamics.

Behavioral epidemic models represent a key departure from the foundational epidemic models, capturing the interdependence between disease progression and individual responses.^{35,43} Several systematic reviews have classified behavioral models into four primary approaches^{52–54}: (1) exogenous models, in which contact patterns or precautionary behavior are externally imposed and do not depend on the epidemic state;^{55–60} (2) endogenous models, where behavior dynamically responds to epidemiological indicators such as incidence, prevalence, or mortality;^{43,61,62} (3) game-theoretic or imitation-based models, where behavior is either the result of individual utility optimization or a diffusion process, spreading from person to person like a second contagion through norms, peer effects, or fear;^{44,63} and (4) empirical models, which directly estimate behavioral responsiveness using real-world data sources such as mobility, surveys, or search trends.^{64–68} Despite growing interest, most models remain either theoretically abstract or empirically untethered, often assuming behavior shifts instantaneously or in stylized ways that fail to reflect real-world decision processes.

Our model integrates endogenous and empirical features by introducing an empirically estimated, locally mortality-responsive behavioral feedback loop. Many prior endogenous models rely on incidence or prevalence as behavioral triggers—for instance, modeling exponential reductions in contact rates as the proportion of infectious individuals increases, or tying risk perception to lagged case reports.^{69–71} While incidence can signal risk, mortality offers a more stable and salient proxy—less prone to underreporting, more publicly visible, and emotionally resonant. Individuals often anchor their risk perceptions around death counts,

especially when reinforced by media or local experience.^{72–75} Our model captures this by linking behavioral change to lagged local mortality, reflecting real-world delays in perception and response. The behavioral responsiveness parameter governing this relationship is empirically estimated, allowing us to quantify the degree of adaptation to risk signals. This structure captures adaptive behavioral dynamics in a tractable and interpretable way—one in which behavior and disease dynamics are explicitly and endogenously coupled.

This modeling strategy provides a practical link between empirical evidence and epidemic modeling. Calibrating behavioral parameters within compartmental models is often infeasible due to data, identification, and computational constraints. Our approach sidesteps these challenges by empirically estimating behavioral responsiveness and introducing it as a feedback mechanism within the Economic-SEIRDS framework.

While our approach offers a tractable and insightful framework, it also has limitations.

Behavioral feedback is likely multidimensional—shaped by media, social dynamics, and national policy—but we model it solely as a response to local mortality. This simplification may overlook other important influences on risk perception. Additionally, although we conduct a qualitative validation against real-world mortality trends, we do not perform a formal statistical validation. Finally, our empirical estimate of behavioral responsiveness reflects average effects and does not capture potential heterogeneity across populations or settings—an important direction for future work. Another limitation is that the behavioral response parameter (θ) is empirically estimated from observed mortality and mobility data during COVID-19. In a future pandemic, real-time estimation may not be immediately feasible, limiting early-stage application of the model.

3.5.1 Prospective Utility of the Economic-SEIRDS Framework in Emerging Epidemics

The key contribution of the Economic-SEIRDS framework lies in its ability to endogenize the effective contact rate based on perceived mortality risk. Rather than treating behavior as static or fully policy-determined, this approach allows the transmission dynamics to evolve in response to epidemic severity—reflecting a behaviorally responsive feedback loop that is grounded in real-time risk perception.

A central parameter in this framework is θ , which governs the elasticity of contact behavior in response to recent mortality. Intuitively, θ captures how sensitively individuals adjust their interactions as risk becomes more salient. Critically, this parameter is context-dependent, influenced by the characteristics of the disease (e.g., severity, latency), information environments, and population-specific behavioral norms.

In the event of a novel epidemic—where real-time behavioral data may not yet be available to estimate θ empirically—the framework remains operationally valuable through a variety of adaptation strategies. First, the model can be deployed in a scenario-based sensitivity analysis, where a range of plausible θ values—based on historical experience (e.g., COVID-19) or structural expectations—can be simulated. This enables early-stage policymakers to explore counterfactual trajectories under weak, moderate, or strong behavioral responsiveness. For instance, simulations could incorporate θ values from -0.05 to -0.20 to reflect varying degrees of behavioral elasticity, providing actionable insight even in the absence of real-world mobility data.

Second, when even rough empirical calibration is not feasible, θ values can be informed through expert elicitation. Drawing on the experience of behavioral scientists, policymakers, and

epidemiologists, a reduced elicitation protocol could be implemented to gather informed priors on population responsiveness to risk. This could be complemented by small-scale survey experiments, conducted in the early phase of the outbreak, to directly elicit anticipated behavioral changes in response to mortality information or perceived infection risk.

Third, the framework can be embedded within a Bayesian updating structure, where an initial prior distribution is assigned to θ —derived from prior epidemics, expert consensus, or theoretical assumptions—and subsequently updated as real-time data become available. For example, early signals from aggregate mobility, self-reported behavior, or policy compliance can inform the likelihood function, allowing the posterior distribution of θ to evolve dynamically. This approach is especially valuable in high-uncertainty environments, enabling probabilistic forecasting and credible intervals for epidemic outcomes rather than deterministic point estimates.

Taken together, these strategies highlight the adaptability of the Economic-SEIRDS framework, which can remain analytically and operationally relevant even in the earliest stages of a public health emergency. Whether through scenario analysis, expert-informed elicitation, or formal Bayesian inference, the model provides a principled structure for incorporating behavioral dynamics into early policy planning—before empirical estimates can be reliably obtained.

Chapter 4: CONCLUSION

This dissertation examines how individuals respond to perceived epidemic risk and how such behavior shapes disease transmission dynamics. By integrating granular empirical evidence with structural epidemic modeling, it advances a unified behavioral framework centered on risk compensation—the idea that individuals adjust preventive efforts based on their perception of threat. Across two distinct but complementary studies, this work contributes both empirical and theoretical insights into the behavioral microfoundations of epidemic spread and the implications of adaptive human responses for policy design and epidemiological modeling.

The first study, presented in Chapter 2, quantifies how perceived mortality risk drives real-time behavioral adaptation. Using high-frequency, county-level mobility data during the COVID-19 pandemic, I show that individuals significantly reduce mobility in response to lagged local deaths. This responsiveness is strongest in discretionary, high-contact domains such as retail and workplace activities, and is distinct from broad mobility trends or seasonality. Importantly, the analysis uncovers a nuanced interaction between endogenous behavior and public policy: shelter-in-place orders and mask mandates amplify, rather than displace, individual preventive behavior—suggesting a crowd-in rather than crowd-out effect. These findings contribute to the growing empirical literature on behavioral epidemiology by isolating objective mortality signals as a causal driver of real-time behavioral change and demonstrating the conditions under which policy and private actions are complementary.

The second study, in Chapter 3, extends these empirical insights into a dynamic economic-epidemiological model that endogenizes contact rates. In contrast to classical compartmental

models with fixed transmission parameters, the SEIRDS model developed here incorporates behavioral feedback: individuals reduce contacts as perceived mortality risk rises. Critically, the magnitude of this feedback is informed by the empirical estimates from Chapter 2, grounding the model in real-world behavioral elasticities. The model reveals that this endogenous feedback generates self-limiting epidemic dynamics—flattening curves, delaying peaks, and in some scenarios producing multiple waves. However, the model also shows that behavioral vigilance is not stable. When pandemic fatigue—modeled as declining responsiveness to mortality risk—is introduced, the feedback loop erodes, leading to higher and more persistent transmission. This highlights a key theoretical insight: the same behavioral mechanisms that stabilize epidemic spread in early phases can become sources of vulnerability over time.

Taken together, the two studies in this dissertation contribute to several literatures. First, they offer a novel behavioral lens on epidemic dynamics by jointly identifying and simulating mortality-responsive risk compensation. Whereas much prior work treats behavior as either exogenous or purely policy-driven, this work shows that private preventive behavior evolves endogenously in response to risk signals, and that public interventions interact with—not substitute for—these dynamics. Second, by calibrating a transmission model with empirically estimated behavioral parameters, this dissertation bridges the gap between behavioral data and structural epidemiological modeling, offering a template for future work that seeks to make theoretical models more behaviorally realistic. Finally, the dissertation offers methodological tools—including mobility domain disaggregation, elasticity-based behavioral coefficients, and a fatigue-aware SEIRDS framework—that can be applied across disease contexts and geographies.

More broadly, this work underscores the need for epidemic models and policy strategies that take seriously the co-evolution of behavior and disease. Forecasting models that fail to incorporate behavioral feedback risk mischaracterizing the timing and scale of transmission peaks. Likewise, interventions that assume linear compliance or stable behavior may fall short in real-world settings where risk perception, fatigue, and private incentives shift over time. Future research should expand these models to account for additional behavioral drivers—such as economic tradeoffs, trust in institutions, or social norms—and extend empirical testing to other diseases and international settings. By embedding behavior into the heart of epidemic analysis, this dissertation contributes to a growing paradigm that views individuals not just as passive recipients of disease or policy, but as active agents whose choices help shape the course of public health crises.

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SUPPLEMENTARY MATERIALS

APPENDIX FOR CHAPTER 2:

Calibrating Category-Specific Mobility at Baseline

To estimate baseline category-specific mobility, we calibrate the fraction of total mobility attributed to Retail & Recreation, Transit, Grocery & Pharmacy, Workplaces, and Parks in the baseline period. This calibration addresses the limitation of SafeGraph data, which provides only total mobility without categorical breakdowns. By leveraging Google's mobility percentage changes and SafeGraph's county-level total mobility data, we derive the fraction of total mobility that corresponds to each category in the baseline period, ensuring consistency between both datasets.

Timeframe for Calibration Model

The calibration procedure is conducted using mobility data from February 15 to March 15, 2020, a period preceding widespread lockdown measures. This timeframe is chosen to ensure that the model captures pre-lockdown behavioral shifts, minimizing disruptions in mobility patterns caused by the onset of the COVID-19 pandemic and the subsequent implementation of public health policies.

Optimization Setup & Methodology

The calibration process estimates category-specific mobility shares by minimizing the squared error between observed log-mobility (SafeGraph total mobility), which serves as the target variable, and the reconstructed log-mobility, derived from category-weighted SafeGraph baselines. This is achieved using the L-BFGS-B algorithm, a constrained optimization approach

that ensures the estimated category probabilities remain non-negative and sum to a value no greater than one.

Let:

- c index counties
- t index time (days)
- $d(t)$ denote whether day t is a weekday or weekend.
- $k \in \{\text{retail\&recreation, transit stations, workplaces, grocery\&pharmacy, parks}\}$
- s_k^d denote the category share for category k for day type d , which we calibrate.
- B_c^d denote the baseline total mobility per 10,000 people in county c on day type d , derived from SafeGraph.
- $\Delta_{k,ct}$ denote the Google-reported percentage change from baseline for category k in county c at time t .
- M_{ct}^{sim} denote the Simulated Total Mobility per 10,000 people in county c at time t .

Then, the simulated mobility is defined as:

$$M_{ct}^{sim} = \sum_k (s_k^{d(t)} \cdot B_c^{d(t)} \cdot \Delta_{k,ct})$$

By combining these elements, we reconstruct total mobility for each time t included in the calibration period (February 15 to March 15, 2020). Note that we calibrate a distinct share for each of the five mobility categories—Retail & Recreation, Transit Stations, Workplaces, Grocery & Pharmacy, and Parks—separately for weekdays and weekends. Since category shares must

sum to one within each day type, we fix the Parks share and calibrate the remaining four, yielding a total of 8 parameters ($4 \text{ categories} \times 2 \text{ day types}$). This weekday/weekend-specific structure is essential because Google's mobility percentage changes are defined relative to day-specific baseline values, capturing systematic pre-pandemic movement patterns. Calibrating shares separately for weekdays and weekends ensures that reconstructed mobility aligns with the structure of the Google mobility data while preserving the internal consistency of total mobility estimates.

Stochastic Initialization

To mitigate convergence issues and avoid local minima in the optimization process, we employ a stochastic initialization strategy. Specifically, we randomly sample 5,000 sets of initial values for category probabilities. The best-fitting set is selected based on the lowest calibration error, ensuring an optimal allocation of total mobility across categories.

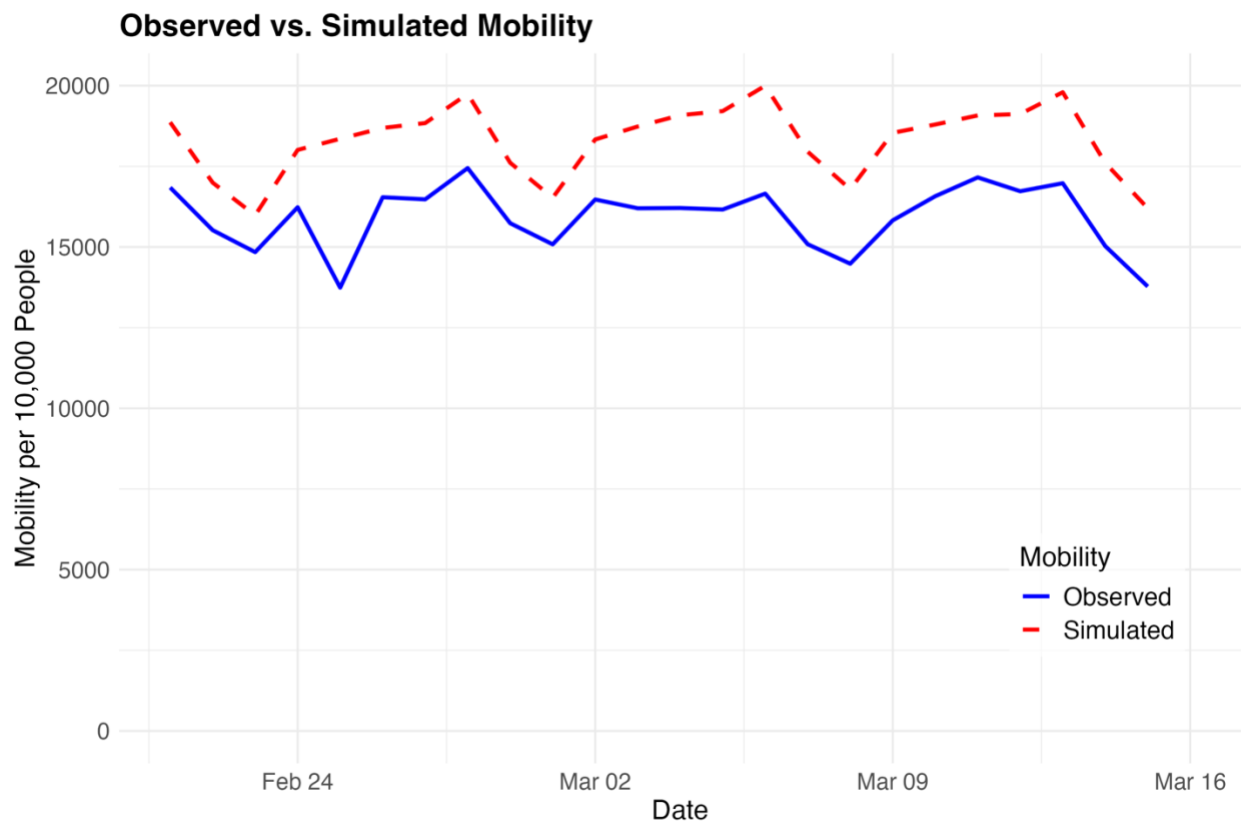
Final Calibrated Output

The final calibrated category shares reflect distinct weekday versus weekend patterns. For weekdays (Monday through Friday), 10% of total mobility is attributed to each of Retail & Recreation, Transit, and Grocery & Pharmacy, 64.85% to Workplaces, and the remaining 5.06% to Parks. For weekends (Saturday and Sunday), we observe increased mobility shares for Retail & Recreation (15.29%), Grocery & Pharmacy (15.13%) and Transit (17.69%), with a corresponding reduction in Workplaces (46.82%), while Parks maintain a fixed residual share of approximately 5.07%. These estimates are reported in the table below:

	Retail & Recreation	Transit Stations	Workplaces	Grocery & Pharmacies	Parks
Weekday	10%	10%	64.85%	10%	5.06%
Weekend	15.29%	17.69%	46.82%	15.13%	5.07%

To validate the fit of our calibration model, we used the estimated category shares presented above to reconstruct simulated total mobility, which we then compare against the observed SafeGraph total mobility for the calibration period. As shown in Figure A1, the simulated mobility closely tracks the observed national average, capturing key trends and fluctuations.

Figure A1: Observed vs. Simulated Total Mobility

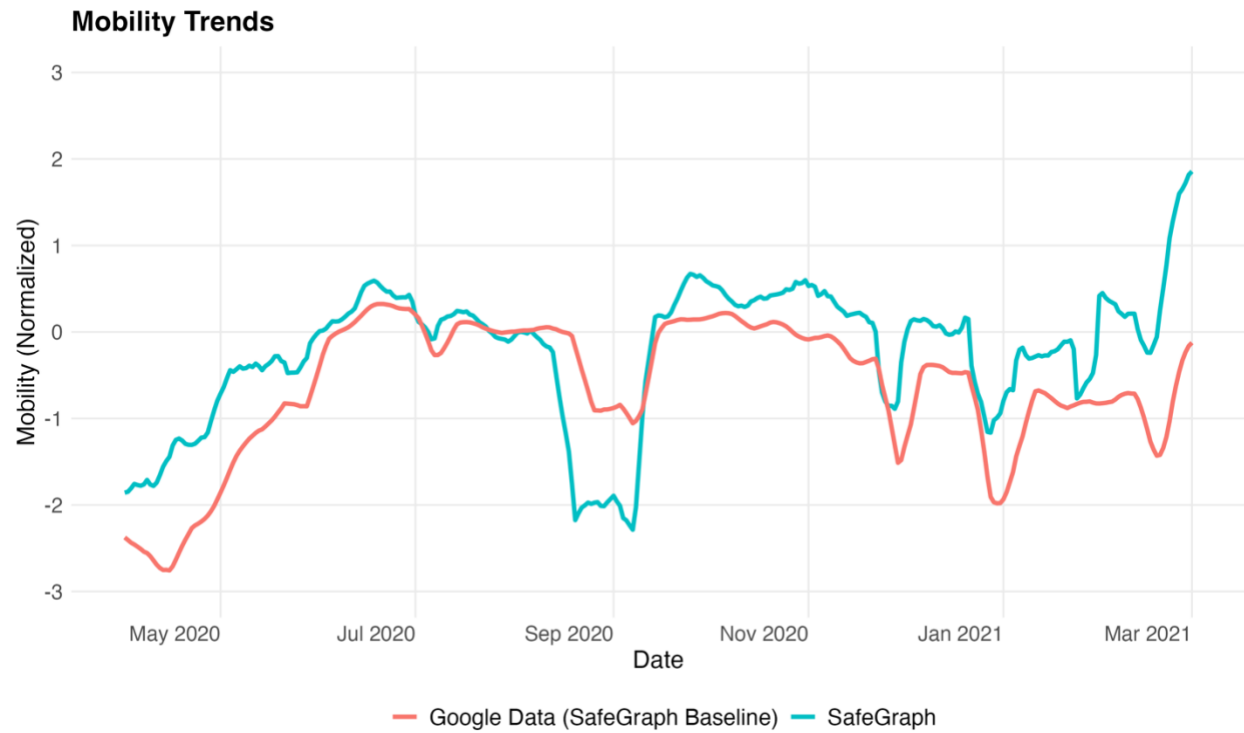


Out-of-Sample Validation Exercise

To assess the validity of our calibration approach, we conduct an out-of-sample validation exercise. Since SafeGraph provides observed total mobility only until March 2021, we leverage the calibrated category-specific shares to reconstruct daily total mobility beyond this period. Specifically, we used the estimated shares to generate category-specific mobility for the out-of-sample period, which we then aggregate to obtain total mobility estimates. These reconstructed mobility trajectories are compared against the observed total mobility reported by SafeGraph.

As shown in Figure A2, the trends, relative changes, and overall patterns of our reconstructed total mobility align closely with the observed SafeGraph mobility data. This alignment indicates that our calibration approach effectively captures the underlying mobility dynamics, reinforcing the robustness of our methodology. The consistency between the estimated and observed mobility suggests that our calibrated shares provide a reliable approximation of category-specific movement patterns, even beyond the calibration period.

Figure A2: External validation: Mobility Trends



APPENDIX FOR CHAPTER 3:

Appendix A: Empirical Estimation of Behavioral Responsiveness Parameter (θ)

This appendix outlines the empirical strategy used to estimate the behavioral responsiveness parameter (θ), which governs the elasticity of contact behavior in response to perceived mortality risk in the Economic-SEIRDS model.

1. Data and Estimation Framework

We estimate θ using a panel dataset of daily county-level mobility and COVID-19 mortality in the United States. Mobility is constructed using harmonized Google and SafeGraph data to generate absolute per capita mobility estimates. COVID-19 death data are sourced from the Johns Hopkins University CSSE dataset, and county population estimates are from the American Community Survey.

We estimate the following fixed effects regression model:

$$\text{Log}(\text{Mobility}_{it}) = \alpha_i + \delta_t + \theta \times \text{DeathsPer10k}_{i, t-7} + \beta X_{it} + \varepsilon_{it}$$

Where:

- Mobility_{it} is total mobility in county i on day t normalized by population.
- $\text{DeathsPer10k}_{i, t-7}$ is the 7-day lagged COVID-19 deaths per 10,000 population.
- θ is the behavioral responsiveness parameter, governing the elasticity of contact behavior with respect to mortality driven risk perception.
- α_i are county fixed effects.
- δ_t are time fixed effects (month and day-of-the week)

- X_{it} includes policy controls (mask mandates, shelter in place) and lagged mobility.

2. Parameter Used in the Model

We used the estimated coefficient for θ during the initial pandemic period, which represents the behavioral response to mortality signals at the outset of the epidemic. The estimated value is $\theta = -0.186$, indicating that each additional death per 10,000 population (lagged by 7 days) is associated with an approximately 18.6% reduction in mobility. This parameter is incorporated into the Economic-SEIRDS model to capture endogenous behavioral responses.

Appendix B: Qualitative Validation of the Economic-SEIRDS Model

To test whether our model plausibly captures epidemic dynamics observed during COVID-19, we conduct a qualitative validation exercise comparing simulated daily deaths to real-world U.S. mortality data from March 1, 2020, to February 28, 2021. While our approach is intentionally stylized and not formally calibrated, we adjust several model parameters to reflect realistic epidemiological conditions during this period (Table B1).

Specifically, we simulated transmission under a time-varying structure of transmissibility to approximate the emergence of major SARS-CoV-2 variants. We first introduced a 30% increase in the transmission probability (ρ) in July 2020 to represent the widespread replacement of the original Wuhan strain by the D614G variant, which became dominant in the U.S. by the summer and was estimated to be significantly more transmissible. We then introduced a second shift in December 2020 to reflect the emergence of the Alpha (B.1.1.7) variant, which both increased transmissibility and enabled reinfections. To capture this, we increased the transition rate from the recovered compartment back to susceptible, mimicking partial immune escape. These modifications allowed us to approximate the timing and transmission environment of the U.S. epidemic in 2020–2021. The parameters used for this exercise are reported in Table B1.

As shown in Figure B1, we compare three epidemic trajectories: one simulated from the traditional SEIRDS model (with static behavior), one from the Economic-SEIRDS model (with behavioral feedback), and observed national COVID-19 deaths (smoothed via LOESS). The traditional model overpredicts the initial peak and fails to reproduce the recurring wave patterns observed in empirical data. In contrast, the Economic-SEIRDS model—by allowing contact rates

to adjust in response to perceived mortality—generates a more dampened, and wave-like progression that more closely aligns with observed patterns. Notably, the Economic-SEIRDS model captures the empirically observed pattern that the second wave of deaths exceeds the first, whereas the traditional model incorrectly predicts the opposite. This alignment provides further face validity for the behavioral feedback mechanism and underscores its importance in reproducing realistic epidemic trajectories.

Figure B1. Comparison of daily COVID-19 deaths across models and observed U.S. data, March 2020 – February 2021

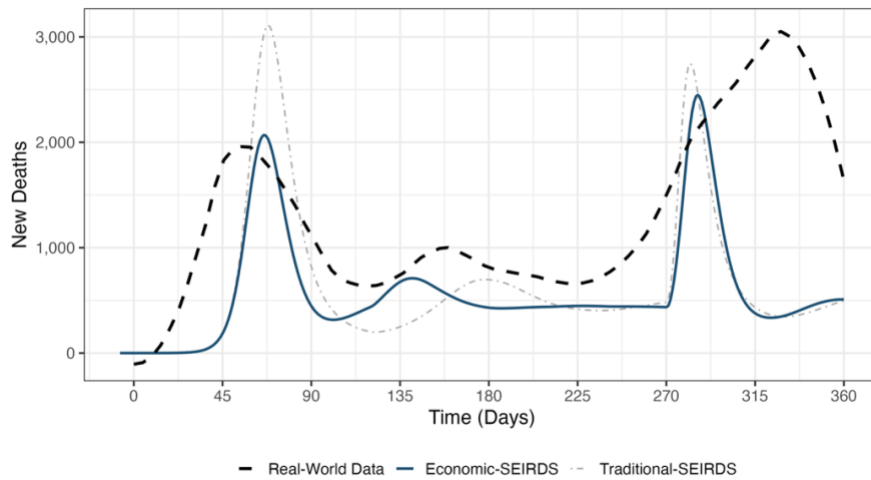


Table B1. Parameter values used for validation simulation (March 2020 – February 2021)

Symbol	Value	Description	Reference
c_0	6.64	Baseline contact rate	Adjusted based on empirically estimated contact rates in the early pandemic phase (March 2020) as reported in Wu et al. (2021). ⁴⁵
θ	-0.186	Behavioral responsiveness to lagged mortality (elasticity of contact rate)	See Appendix
ρ_0	0.1073	Probability that a contact leads to infection	⁴⁵
ρ_1	$\rho_0 \times 1.32$	Increased transmissibility due to D614G variant (July 2020)	⁷⁶
ρ_2	$\rho_0 \times 1.32 \times 1.90$	Increased transmissibility due to Alpha variant (Dec 2020)	⁷⁷

σ	1/5.2	Rate of progression from exposed to infectious (mean incubation: 5.2 days)	⁴⁵
γ	1/7	Recovery rate (mean infectious duration: 7 days)	⁴⁵
δ	0.008	Daily disease-induced mortality rate among infectious individuals	^{45,78}
ω	1/120	Rate of waning immunity (average immunity duration: 120 days)	⁵¹
μ	0.000027	Natural birth/death rate	Based on CDC estimate (0.98% annual natural mortality)