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Individual Behavior and Policy Response in Times of a Pandemic

SVEUČILIŠTE U ZAGREBU

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Abstract

This paper presents a comprehensive analysis of the intricate dynamics between policy stringency, human behavior, and pandemic outcomes during the COVID-19 crisis. Drawing inspiration from the 'Taylor rule', we develop and estimate a theoretical C-SI (Cases - Stringency Index) model, providing policymakers with an intuitive framework to assess the efficacy of economic and health policies enacted in response to the pandemic. Our C-SI model considers the interplay between formal stringency measures and individual behaviors, recognizing the nuanced factors influencing decisions to adhere to restrictions. Through rigorous theoretical development and empirical testing using a three-stage least squares (3SLS) approach we investigate the endogenous interaction between policy instruments, individual behavior, and pandemic outcomes. Our results underscore the significant influence of public interest in COVID-related topics, or the "fear factor," on individual behavior, suggesting that this factor rivals/complement formal stringency measures in shaping behavior. We identify a clear trade-off between economic and health outcomes and we observe a nonlinear relationship between stringency and mobility, indicating that changes in stringency measures do not consistently correlate with changes in behavior. Our analysis reveals no evidence of stringency policy endogeneity while we find strong evidence that vaccination rates exert a strong influence on policymakers across all analyzed states.

Key words

COVID-19; policy effectiveness; policy-maker preferences; endogeneity

JEL classification

C22, E70, H75, I12, I18

Individual Behavior and Policy Response in Times of a Pandemic

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Abstract

This paper presents a comprehensive analysis of the intricate dynamics between policy stringency, human behavior, and pandemic outcomes during the COVID-19 crisis. Drawing inspiration from the 'Taylor rule', we develop and estimate a theoretical C-SI (Cases - Stringency Index) model, providing policymakers with an intuitive framework to assess the efficacy of economic and health policies enacted in response to the pandemic. Our C-SI model considers the interplay between formal stringency measures and individual behaviors, recognizing the nuanced factors influencing decisions to adhere to restrictions. Through rigorous theoretical development and empirical testing using a three-stage least squares (3SLS) approach we investigate the endogenous interaction between policy instruments, individual behavior, and pandemic outcomes. Our results underscore the significant influence of public interest in COVID-related topics, or the "fear factor," on individual behavior, suggesting that this factor rivals/complement formal stringency measures in shaping behavior. We identify a clear trade-off between economic and health outcomes and we observe a nonlinear relationship between stringency and mobility, indicating that changes in stringency measures do not consistently correlate with changes in behaviour. Our analysis reveals no evidence of stringency policy endogeneity while we find strong evidence that vaccination rates exert a strong influence on policymakers across all analysed states.

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1. Introduction

In this paper we develop and estimate theoretical C-SI model as an intuitive tool for analyzing the effectiveness of economic and health policies implemented during the COVID-19 pandemic. We adopt a framework reminiscent of the 'Taylor rule' wherein policymakers utilize the stringency level as a policy instrument, navigating a delicate trade-off between health and economic outcomes (Sonora 2022). It is assumed that formal stringency measures only imperfectly alter human behavior, which in terms is assumed to influence both health and economic outcomes.

At its root, the decision to stay home during the COVID-19 crisis can be divided into two sub-behaviors, those influenced by the policy to restrict the movements and minimize the risk of spreading, and unobserved idiosyncratic individual choice that is the function of the set of available and beliefs of each individual.

Cervantes et al (2022) and Celsa-Arellano et al (2023) already modelled and estimated impact of COVID induced panic on financial markets. Expanding on their concept, we incorporate the influence of news and/or panic on health and economic outcomes via their impact on idiosyncratic component of human behavior. This modelling strategy broadens the array of tools available to policymakers, recognizing that targeted communication strategies could complement or serve as alternatives to formal restrictions.

By constructing and applying a model that analyzes these interactions, policymakers can gain valuable insights into relative effectiveness of policy instruments and how different interventions health and economic outcomes. The significance of the model is in shedding light on stylized empirical facts related to the COVID-19 pandemic. The inclusion of the news effect within the model provides a valuable theoretical and empirical framework for examining the diverse approaches adopted by different countries in managing the pandemic. For instance, it facilitates analysis of China's strategy, characterized by stringent total lockdown measures in affected regions, as well as Sweden's approach, which primarily relies on recommendations and communication tools rather than strict mandates (Figure 4).

The model also aims to shed light on the significant differences in death rates observed among countries with comparable levels of development and similar quality of data reporting and/or lack of negative correlation between stringency index and death rates across countries. For instance, South Korea reported approximately 665 deaths per million residents, contrasting sharply with the Czech Republic, a nation with a similar per capita real GDP, where the figure stood at

3,967 per million. Similarly, Portugal recorded 2,575 deaths per million residents, while Croatia, a Mediterranean country with comparable development levels, experienced almost double that figure, at 4,381 deaths per million. In the United States, where healthcare expenditure as a share of GDP is the highest, the death rate reached about 3,410 per million, highest among western economies (Figure 5 and 6).

Furthermore, the model also accounts for instances where the number of reported cases exhibits an immediate response to stringency measures, contrary to the expected delay dictated by the virus's typical incubation period. For example, in the December 2020. after a more than a week-long campaign to raise awareness and build public support, the number of cases dropped immediately after the announcement of new measures of social distancing (Figure 7).

We start with development of the C-SI (*Cases - Stringency index*) theoretical model with four endogenous variables: stringency index as a proxy for the behaviour of policy makers, index of mobility of population as an proxy for the individual behaviour and two outcome variables for number of COVID cases and unemployment.

In order to make theoretical analysis as intuitive as possible we develop the model within the framework of comparative statics traditionally used by economists. We use mathematical system of four equations with four endogenous variables to derive slopes and shifts of two curves in the two-dimensional space. The derived graphical representation of the system of equation is methodological similar to IS-LM model and it can be quite intuitively used to explore predicted outcomes of various policies and shocks. In the theoretical part we graphically explore the effects of economic shocks, shocks in vaccination rates and news (panic) effects on the model.

The empirical model is tested with a four equation system using three stage least squares (3SLS). The modeling methodology allows us to account for endogeneity across the behavioral and outcome variables to investigate the endogenous interaction between the behavioral and outcome variables. Our two year sample period is weekly and begins in February 2020. Due to limited availability of weekly data for economic indicators during the period of interest (2020-2023), we have decided to estimate our model on the data for four largest US states. Google's phone data helps us to track mobility and identify patterns of idiosyncratic behavioral changes: mobility should decrease as stringency increases and differences in preferences across the states should lead to idiosyncratic responses to policy recommendations. We study the properties of unobserved individual behavior; the estimated residuals from a model of mobility conditional on policy restrictions for each state in the sample. The residual represents the unobserved mobility preferences of individuals and is an indicator how closely individual and policy-maker preferences align.

The COVID pandemic of 2020-2023 provides researchers with a unique opportunity to observe both individual behavior as well as policy-makers decisions. We use weekly cell phone mobility data and an index of behavioral policy restrictions to investigate how effective policy is at modifying individual's behavior to meet a goal. Following out theoretical model, our empirical 4×4 model also includes two behavioral variables, the policy instruments and individual behavior, and two "outcome" variables, COVID cases and unemployment. The news (the "fear factor") effect as potential alternative policy instrument is included as exogenous variable. We also include a number of other exogenous variables in our estimates in order to control for vaccination rates, climate, hospital capacity, etc.

While our estimation results vary among states, we can still derive some overarching conclusions from the empirical model. Firstly, our results highlight the substantial influence of public interest, or the "fear factor," in shaping individual behavior during the pandemic. This factor emerges as a formidable driver of behavior, rivaling the impact of formal stringency measures in shaping public responses. Additionally, we observe a nonlinear relationship between stringency measures and mobility patterns, suggesting that shifts in policy stringency do not consistently correspond with changes in mobility. Moreover, our analysis uncovers no evidence of policy endogeneity, suggesting that mobility does not significantly sway policy decisions, which aligns with the results found in Sonora and Gottwald-Belinić (2023). Secondly, we identify a pronounced trade-off between economic prosperity and public health outcomes, underscoring the complex decisions policymakers must navigate, similar in spirit to result found in Sonora (2022). Lastly, vaccination rates emerge as a significant influencer of policy decisions across all states, prompting reductions in stringency measures.

The remainder of the paper is organized as follows. Section 2 discuss how policy effectiveness is defined in the paper. Section 3 develops theoretical model; Section 4 provides an overview of the methodology and discusses the data. In Section 5 we present the empirical results, and Section 6 concludes.

2. Policy Effectiveness

Herein lies the crucial research question: how effective is policy? To determine this we must first define it. We define policy effectiveness by how closely it is followed by the policy-makers constituents. This definition does not necessarily mean the policy will be successful at achieving its goals, but whether or not they were adhered to. A presumption of this definition is that policy-makers to have a policy goal which is socially beneficial, for example, preventing a majority of the population from getting COVID and not a random whim of the regulator.[2]

According to Potter and Harries (2006) the "determinants of policy effectiveness" for health policy models requires public administration system to include diverse social, cultural and economic motivators engaged in behavior. A state of pandemic represents a rare opportunity to empirically analyze individual behavior during a period of lock-down and public fear and behavioral respond to changes on policies intended to minimize infection rates and protect the health of the residents (Heuring (2021)). According to the survey made among the citizens across the United States in May 2020, the reaction on widespread support to stay-at-home policies were actively accepted among the majority of the surveyed residents Czeisler et al. (2021). Individual reactions went even beyond the intended policy. People indicated that they would feel unsafe if restrictions were lifted. The anxiety level and concerns about the impact of disease on individual health as well as the health of their peers triggered risk averse behavior in population.

We therefore couch the discussion in terms of policy effectiveness. To determine whether or not a policy is effective is defined by how closely residents follow the prescribed restriction. This requires the designer to also understand the preferences of her constituents. Thus, as in Brainard (1967), we can consider policy effectiveness, for any time t, compactly in the relationship

$$B_t = \theta_t P_t + u_t, \theta \geq 0 \tag{1}$$

where individual behavior is represented by B, P represents the policy in question, and u represent other exogenous factors influencing an individuals actions. If policy is *effective*, regardless of whether or not it is the *correct* policy, implies the policy response parameter, θ, is greater

[2] An example of policy making on a whim with no social benefit occurred about 50 years ago in Myanmar when then dictator U Ne Win suddenly introduced right-hand traffic after years of left-hand traffic on the advice of an astrologer to prevent bad luck.

than or equal to 1. That is the optimal policy is one such that

$$B_t^* = P_t^*.$$

If any given individual ignores the policy $\theta = 0$. On other hand, others may believe the policy does not go far enough and $\theta > 1$. Aggregating over the all individuals it reasonable to assume that the average policy response is given as $\bar{\theta} \leq 1$. Note that θ and P are time dependent representing that new information may change both policy and individual's policy responses. In this context, deviations from the prescribed policy are given in u which reflects individual's set of preferences and animal spirits. u also represents individual's level of understanding of what is being asked of them and also reflects a lag between the policy announcement and the behavioral adjustment.

Alternatively, policy must also consider the preferences of households,

$$P_t = \lambda_t B_t + e_t, \lambda \leq 1$$

where λ represent the policy-maker's understanding of her constituents preferences and e represents exogenous new information or factors which force the policy to deviate from what they believe their constituents will follow. The policy-maker must recognize what level of restrictions is feasible to impose otherwise residents will not take it too seriously. The better the policy-makers knows her constituents the more likely the policy-maker will achieve her goals. It is important to note that, in this discussion, the policy may *not* be the best policy to achieve the goal. Rather it is a function of how well the policy-maker understands her constituents. Thus, policy effectiveness is defined as what can feasibly be implemented and whether or not individuals will buy into any restrictions. It is also a function of how enforceable the policy is, if the cost of monitoring behavior is too high, constituents may be willing to flaunt the new rules, rendering it ineffective.

Therefore, in order for policy to be effective individuals have to believe the policy-maker and the policy-maker has to understand her constituents. This implies there is a feedback loop between individual behavior and policy decisions. Recently, Sonora and Gottwald-Belinić (2023), estimated a version of equation (1) for the 10 largest US states and assumed that policy was exogenous. They demonstrated that policy is followed, but it can take up to 1.5 years to be 100%

effective. Perhaps of more realistically, they found that for policy to be 50% effective it took between 150, in Texas, to 500 days in Pennsylvania – in the context of equation (1), $\theta_{TX} > \theta_{PA}$.

What this paper did not answer, however, is how well was the policy designed given resident's preferences, that is the level of λ. Did the time required for policy to be effective reflect households willingness to adapt to the policy restriction? Or was it that in some states, the policy-makers better understood their constituents? Or some combination of the two? By endogenizing these two processes, we can analyze the relationship between policy construction and resident responses to better understand the dynamics of policy effectiveness.

3. Introducing the theoretical $C - SI$ model

We begin our analysis by introducing a formal theoretical model to analyze the interaction between policy-maker and resident preferences. In this model, the revealed preferences of each agent are manifested in stringency policy, si, for policy-makers and mobility. Because COVID is an outcome of transmission, via mobility and density, the model is discussed in policy-COVID space.

We start with general system of equations with four endogenous variables: the policy stringency index si; the change in COVID c, defined either in terms of cases or deaths; an index of individual mobility, gmi; and the unemployment rate u which is a gauge for economic activity. Exogenous shocks in our systems are news (in terms of Google searches) gs, the vaccination rate v and economic conditions ec.

The general form of the model is the system of equations:

$$
\begin{aligned}
si &= si(\overset{(+)}{c}, \overset{(-)}{u}, \overset{(+)}{gmi} \mid \overset{(-)}{v}) && (2)\\
gmi &= gmi(\overset{(-)}{c}, \overset{(-)}{si}, \overset{(+)}{u} \mid \overset{(+)}{v}, \overset{(-)}{gs}) && (3)\\
c &= c(\overset{(+)}{gmi}, \overset{(-)}{u} \mid \overset{(-)}{gs}, \overset{(-)}{v}) && (4)\\
u &= u(\overset{(-)}{gmi}, \overset{(+)}{si} \mid \overset{(-)}{ec}) && (5)
\end{aligned}
$$

where positive and negative signs represent the sign of the partial derivative, e.g.

$$
\begin{aligned}
si =& si(\overset{(-)}{c}, \cdot) \Rightarrow \frac{\partial si}{\partial c} > 0 \Rightarrow si_c > 0,\\
c =& c(\cdot, \overset{(-)}{u}, \cdot) \Rightarrow \frac{\partial c}{\partial u} < 0 \Rightarrow c_u < 0.
\end{aligned} \qquad (6)
$$

Equation (2) is the *policy* function. We assume: the number of cases increases stringency $si_c > 0$; an increase in mobility of population will induce policy-makers to increase stringency $si_{gmi} > 0$ (unless there is accommodating policy making); rising unemployment creates pressures to soften stringency $si_u < 0$; and the vaccination rate is an alternative for stringency measures, $si_v < 0$

Equation (4) defines changes in the number of cases. We assume that mobility increases the spread of the virus, $c_{gmi} > 0$; while unemployment, greater pandemic information seeking; and vaccination rates reduce cases, $c_{\aleph} < 0$ where $\aleph = u, gs, v$.

Equation (3) captures individual resident behavior (mobility) and its determinants. We assume that stringency measures and number of cases reduces mobility, $gmi_{si} < 0$ and $gmi_c < 0$. We also assume that the "fear factor" parameter, captured by information gathering is also negative, mobility in this case, $c_{gs} < 0$. Unemployment and the vaccination rate are assumed to have positive effects, $gmi_u > 0$ and $gmi_v > 0$.

Finally, we model the function for the state of the economy in equation (5). We assume that unemployment rate is driven by general economic conditions $u_{ec} < 0$ and that the restrictions affect unemployment positively, $u_{si} > 0$, while the reaction of population to stringency proxied by mobility has opposite sign $u_{gmi} < 0$. Increase in mobility raises demand for labor and decreases unemployment.[3]

Besides the assumed theoretical signs of coefficients it is important to pay attention to absolute size of effects. For example, if reaction of stringency to change in number of cases is less than one in absolute terms $|si_c| \in (0, 1)$, we can conclude that policy-makers are risk taking. On the other if the response of mobility is less than one $|gmi_c| \in (0, 1)$ we can conclude that individuals are risk taking as well. The values above unity $si_c > 1$ and $|gmi_c| > 1$ would imply that they are risk averse. From the perspective of individuals, similar logic can be applied to the fear factor coefficient gmi_{gs}.

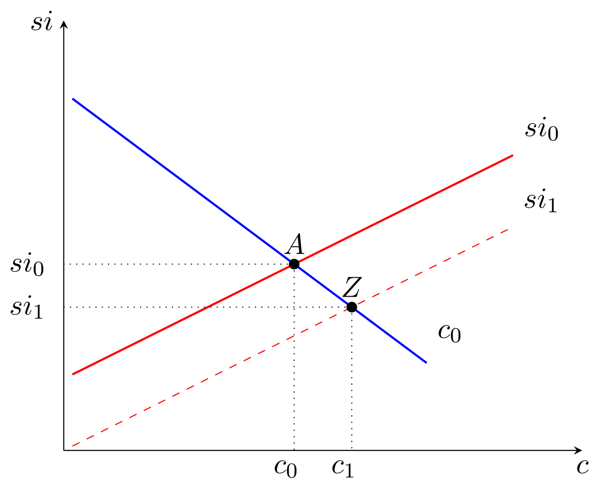
In order to build intuition around the model, we use $IS - LM$ style comparative static analysis where we analyze effects of exogenous shocks on the stringency index and number of cases. Formally, in the derivation of the model we keep all four variables (stringency, cases, mobility and unemployment) endogenous, but due to limitation of two-dimensional figures, the

[3] We assume that working from home labor supply and online commerce can not substitute shock completely.

stringency index is on represented on the $Y-$axis and COVID are on the $X-$axis.[4].

We start the graphical analysis of the theoretical model with a shock that deteriorates economic conditions. According to Sonora (2022) such a shock would induce Taylor rule choice between stringency and economic deterioration and - depending on the preferences of policy-makers - might induce downward shift of si curve. Clearly, some policy-makers will be willing to have more cases and therefore have less stringency, which is shown by a shift in the policy curve from si to si_1 which yields lower stringency and more cases.

Figure 1: Effect of economic shocks in the $C - SI$ model



This phenomenon was demonstrated in Sonora (2022) who used a COVID loss function to show that some states were willing to accept more cases to preserve the economy while others stressed reducing COVID. His results found that Florida and Texas were consistently more economy-centric than New York and California.

The result of exogenous deterioration in the labor market would *ceterus paribus* result in higher number of cases and lower stringency index. As suggested by authors, strength of such policies is off course dependent on the preferences of policy-makers and hospital capacities to deal with more cases.

Second shock that we address is the increase in vaccination rate that will shift si curve downwards and c curve leftward. Intuition for the shift of si comes from the fact that rise in vaccination rate will affect stringency directly through expectations of policy-makers and indirectly through the drop in COVID cases and increase in mobility (we assume that the effect

[4]See Appendix A for the formal derivation of the slopes and shifts of the $C - SI$ model

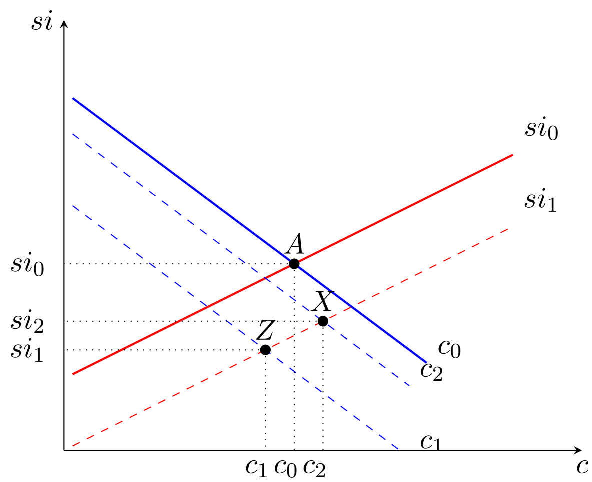
of the drop in COVID cases dominate over the effect of the rise in mobility).

When it comes to c curve it will shift to the left, since rise in vaccination rate will reduce number of COVID cases for each level of stringency. Again we assume that vaccination effect dominates the fact that people will get more active once they get vaccinated.

As a result we will end up with lower stringency level for each number of COVID cases (Figure 2). While the change in number of COVID cases in the new equilibrium will depend on the strength of the relative shifts of si and c. If the shift of si curve is bigger, the model will end up in equilibrium X with higher number of cases and *vice versa* if the shift of c curve is stronger, the number of cases will be smaller in new equilibrium Z.

Intuitively, the relative size of shift will depend of the ratio of expected drop in cases relative to the actual drop in cases and indirectly on the relationship between vaccination rate and mobility of vaccinated and general population. The stronger the effect of vaccination is on transmission of COVID and the weaker is the effect of vaccination on the mobility of people, drop in COVID cases in more probable in the new equilibrium for a given change in stringency.

Figure 2: Vaccination rate shift in the $C - SI$ model

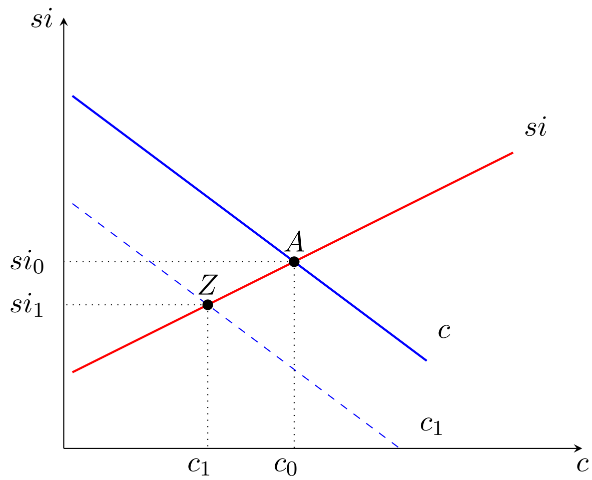


Finally we explore the effect of the so called fear factor or frequency of COVID related news. We can assume that COVID related news and other COVID related media or social network activities will have impact on behavior of people. For example, rise in awareness of COVID related dangers might decrease mobility of people and transmission in general (social contacts, washing hands, wearing masks, etc.) and number of cases for given stringency level.

In terms of our model, that would imply shift of the c curve to the left, implying lower level of cases and lower stringency in the new equilibrium (Figure 3). The intuition is based on the assumption that frequency of COVID related news and information related to COVID in general affect behavior of the population and changes the speed of the transmission in the similar way as formal stringency rules.

In terms of policy making, effect of news is important due to the fact that it's effects on COVID cases are opposite relative to the case of reaction of policy-makers to economic slowdown.

Figure 3: Effect of news in the $C - SI$ model



4. Methodology and Data

4.1. Methodology

We employ three stage least square estimator in order to estimate empirical model with four endogenous variables: stringency index si_t, mobility index gmi_t, change in COVID cases Δc_t and unemployment rate u_t:

$$si_t = s_0 + s_1 si_{t-n} + s_2 \Delta c_{t-n} + s_3 \hat{u}_t + s_4 \hat{u}_{t-n} + s_5 gmi_{t-n} + s_6 v_{t-n} + s7beds_{t-n} + \epsilon_t \quad (7)$$

$$gmi_t = g_0 + g_1 gmi_{t-n} + g_2 \Delta c_{t-n} + g_3 si_{t-n} + g_4 si^2_{t-n} + g_5 \hat{u}_{t-n} + g_6 v_{t-n} + g_7 gs_{t-n} + \eta_t \quad (8)$$

$$\begin{aligned} \Delta c_t &= c_0 + c_1 \Delta c_{t-n} + c_2 gmi_{t-n} + c_3 u_{t-n} + c_4 (gmi_{t-n} * (1 - v_{t-n})) + c_5 v_{t-n} + c_6 gs_{t-n} \\ &+ c_7 seas_{t-n} + c_8 Biden_t + \psi_t \end{aligned} \quad (9)$$

$$u_t = v_0 + v_1 u_{t-n} + v_2 gmi_{t-n} + v_3 si_{t-n} + \phi_t \quad (10)$$

where v_t represents vaccination rate, si^2 is squared stringency index (nonlinear effect), gs_t is the news effect, $1 - v_t$ is non-vaccination rate, $beds_t$ are hospital utilization rate, $seas_t$ is dummy variable for summer (proxy for temperature oscillation), $Biden_t$ is time fixed effect which represent the change in federal COVID policy after President Biden was inaugurated and ϵ, η_t, ψ_t and ϕ_t represents error terms in estimated equations. All variables are in logs with exception of vaccination rate v_t and unemployment rate u_t that are expressed as percentages.

Equation (7) models behavior of stringency index and in a way represents behavioral model of the policy-makers. Equation (8) represents the behavioral model of the individual agents measured by the mobility index. In the equation (9) the dynamics of pandemics is modeled measured by the change in COVID cases or deaths. Finally in equation (10) we model impact of the pandemics onto economic conditions proxied by unemployment.

We model nonlinear effects of stringency index on individual behavior in two ways [Equation (8)]. First, we allow for concave/convex response of mobility to stringency with square terms si_{t-n} and si^2_{t-n} and after that we estimate model with sample split analysis where we measure response of mobility to stringency in two regimes $D_t si_{t-n}$ and $(1 - D_t)si_{t-n}$ where $D_t = 1$ if change in stringency index is positive, $\Delta si_t > 0$, and zero otherwise.

We estimate equations 7 through 10 using a three-stage least squares (3SLS) GMM estimator based weighting matrix:

$$\dot{W} = \left(N^{-1} \sum_{t=1}^{N} Z_t' \hat{\Omega} Z_t \right) \tag{11}$$

where $\hat{\hat{u}}_i$ are estimated residuals from the initial two stage (2SLS) and $G \times G$ matrix of residuals is defined as:

$$\hat{\Omega} \equiv N^{-1} \sum_{t=1}^{N} \hat{\hat{u}}_t \hat{\hat{u}}_t' \tag{12}$$

and estimated coefficients using 3SLS are defined as:

$$\hat{\beta} = [X'Z\dot{W}Z'X]^{-1} X'Z\dot{W}Z'Y \tag{13}$$

The estimated $\hat{\beta}$ is defined such that it is consistent and asymptotically normal.

4.2. Data

Our data is weekly and the sample is the two year period February 2020 to February 2022, which roughly coincides with the end of the omicron variant spike. To simplify the presentation of the analysis we choose the four largest states in terms of gross state product (GSP). In descending order the states are: California (D), Texas (R), New York (D), and Florida (R). There are differences in the way Democrat (D) and Republican (R) Governors responded to the pandemic and our sample includes a balanced mix of the two parties.

To proxy for individual mobility behavior we use recently available cell phone data to observe movements. Google's Community Mobility Report (Google (2021)) indexes six different "types" of mobility, by state: Grocery and pharmacy, retail and recreation, parks, residential, work, and transit. We use the daily mean of *five* of these indices to derive an overall index of mobility, the Google mobility index (GMI).[5] The index is defined as the percentage difference between the mobility on any given day based on pre-pandemic mobility, $GMI \in (-100\%, 100\%)$. We exclude "park" mobility – defined as "...trends for places like national parks, public beaches, marinas, dog parks, plazas, and public gardens, see Google (2021) – for two reasons. First, stringency measures are designed to *restrict* movement and with many areas being closed off, outdoor mobility will rise as there are few other locations to go outside the home. Secondly, from a data standpoint, the park index varies greatly across the states. In Ohio, mobility in parks averaged about 130% above pre-pandemic levels.

Two other mobility indices were also considered. The first is the Dallas Federal Reserve Bank's Mobility and Engagement Index derived from cell phone tracking data. However this data was discontinued in late-March of 2021 which limits the time series length and would exclude some important structural changes in national COVID policy, such as the vaccine being readily available to all residents over the age of 18. A second alternative is produced by Apple called the Mobility Trends Report, Apple (2021). We chose not to use this index because it is constructed from users of iPhones, which could bias results given that iPhone users are generally more urban, higher income, and better educated, see Hixon (2014).

COVID restriction policies are from the Oxford Coronavirus Government Response Tracker (OxCGRT) Stringency Index (denoted $OxSI$) (Hale et al. (2021)). This one of the several indices constructed by OxCGRT but was chosen as it quantifies the degree to which states restrict individual movements, via "lockdown" policies, rather than economic support or health containment policies. The index is between 0 and 100 with a value of 100 being the most

[5] We also tried a principle components approach. Because the correlation between the mean and principle component index was over 0.94 for all states we chose to use the mean as the calculation is more transparent.

restrictive. The index represents all containment and closure policy indicators, such as school and workplace closing, public events cancellation and restrictions on gathering, public transport access restrictions, and travel restriction incorporated with stay at home promotions including the proxy for recorded public information campaigns. OxCGRT daily data captures the intensity and modality on policy interventions for COVID-19. The stringency index shows variation within regions and states, correlated with political determination of particular state government.

The per-capita case and death data is from the John Hopkins Coronavirus Resource Center, Dong et al. (2020), available from Johns Hopkins University (2021). The weekly unemployment data used is the insured unemployment rate, from the U.S. Employment and Training Administration (2021), and is the percent of the insured labor force that is continuing to file for unemployment insurance. The long run unemployment rate, $\bar{u}$, is the average of the insured unemployment rate from January 1, 2019 – January 21, 2020, the pre-pandemic normal. While not strictly the commonly used definition of unemployment, we will call this variable unemployment throughout the paper. To control for changing healthcare infrastructure we use hospital bed vacancy rates, also from Johns Hopkins (2021). This accounts for i. policy-makers not wanting to over-burden hospitals with new cases and ii. access to healthcare for COVID patients. Secondly, we include the current and one-week lagged percentage of eligible population which has been vaccinated, $\%VAX$, at least once.

A time fixed effect effective the date of the Biden administration's inauguration on January 20, 2021 which signaled a shift in national COVID policy, discussed before the election by Malakoff (2020) with differences later highlighted in Kates et al.. Finally, seasonal fixed effects are also included: The first is a summer indicator, June 1 to September 1 for both 2020 and 2021. The second is a winter holiday season variable extending from October 1 to January 15. The 2021 Texas power crisis, February 10-27, 2021 is also included in the Texas model as this had a significant impact on mobility in the state.

Lastly, for policy-makers and residents seeing information on COVID we use state level internet search data from Google Trends, Google (2022). This captures information, particularly concern about the spread of COVID, seeking and is assumed to alter both policy-maker and resident decisions. The data is the number of weekly searches for "COVID" from users of the Google search engine.

Table provides the mean, standard deviation (SD), the minimum and maximum of the GMI

and $OxSI$ data by party of the governor and for each state. States with a Republican governor had fewer restrictions and more overall mobility. The GMI averaged -15.6 and -11.2 and the $OxSI$ averaged 53.1 and 47.7 for Democrat and Republican governor states respectively. The state with highest mobility is Oho and the least mobility is in New York while the least/most stringent states are Florida and New York. It is also worth noting that states governed by either party followed similar policy responses across party lines, indicated by comparable $OxSI$ standard deviations. However, there is greater differences in mobility behavior in Democrat states than Republican ones. Republican led states have more mobility and less stringency than Democrat states. Interestingly, at the end of the sample period Democrat led states have less stringency than Republican states. This is likely because of the surge in new cases in non-vaccinated residents due to the Delta variant of COVID which primarily impacted Republican states. We can also see the effect of severe weather that precipitated the Texas power problem in February, 2021. Holiday mobility can also be seen to decline.

5. Results

We present the results of the estimated equations (7) through (10) in Table 3 for registered COVID cases and Table 4 for registered COVID related deaths. Table 3 presents results for each state in separate column, while results for equations (7) through (10) are separated by horizontal lines.

Results for equation (7) are showing strong level of persistence in stringency index indicating gradual changes in pandemic related restrictions. Another robust results is for vaccination rate where we have estimated negative and statistically significant result in all states.

When it comes to response of stringency to change in cases, we have got intuitive results for Florida and California, while results for New York and Texas are not significant. When it comes to the effect of unemployment lagged results are negative in all states with exception of California. Indicator of hospital beds utilization is only marginally significant in Texas and California.

Obviously such results imply that policymakers change policies in gradual way, that the vaccination rate influenced their behavior in all analyzed cross sections regardless of the narratives. Besides that we are able to find evidence of a loss function were policy-makers were trying to minimize losses relative to unemployment and COVID cases depending on their relative preferences.

With respect to equation (8) that models individual behavior results also indicate high level of persistence. Results indicate strong and robustly negative effects of the growth rate of COVID cases and news effect as well. Obviously individual behavior was affected with data on the spread on pandemics, but also on the awareness of the population about existence of pandemics (gs_t variable is proxied by google search statistics about COVID).

Vaccination rate is also important in explaining mobility and estimated coefficient has positive sign in all states with exception of New York. When it comes to nonlinear effects, we have estimated nonlinearity in all states with exception of Florida. In Figure 9 we provide visualization of the estimated coefficients for si_{t-n} and si^2_{t-n}. The results suggest that the strength of the effect of stringency on the individual behavior (measured by mobility index) depends on the level of stringency (on history of stringency measures).

The third section of the Table 3 presents results of the equation (9). Mobility index and interaction term between mobility and non-vaccination rate have positive effect on the pandemic dynamics, while vaccination rate has negative effect over all cross-sections. When it comes to effects of summer $seas1_{t-n}$ and the change in federal COVID policy $biden_{t-n}$ we have only marginally significant results.

When it comes to modeling economic situation we have modeled unemployment as a function of mobility, stringency and wider economic conditions, equation (10). Results show evidence that deterioration of economic activity as measured by unemployment was predominately driven by swings in the mobility of population. Estimated coefficient is robust and negative in all states with exception of California. In the California, results is driven by economic conditions index. As all other three results, we have also evidence that unemployment is strongly persistent variable.

Table 4 presents results for the model in which growth rate of COVID cases is replaced by growth rate of COVID related deaths. Qualitatively, results are the same as in Table 4. The major differences are in the fact that estimated coefficients for nonlinear effects of stringency on mobility are at different levels of significance. In the case with death related statistics estimates for California are not statistically different from zero, while estimate for Florida is statistically significant. The visualization of estimated coefficients si_{t-n} and si^2_{t-n} is presented on Figure 10.

We have also estimated nonlinear relationship between stringency and mobility using sample split technique. We have estimated two separate coefficients, one for the positive change in stringency $upsi_{t-n}$ and another for negative change in stringency $downsi_{t-n}$. Results are presented in Table 5. Both coefficients are insignificant in most of the states, and in California they are not statistically different between two regimes.

6. Conclusion

In this paper we use a system approach to gain insight into policy-maker and resident behavior during the 2020-2022 COVID pandemic. Unlike previous research into the responses of policy-makers and residents which took the other's decisions as exogenous, this paper endogenizes policy-maker and resident behavior.

We begin by constructing a theoretical model which allows to provide some background into how the two sets of preferences respond to each other and with a two other outcome endogenous variables: the economy and COVID cases. We then applied three stage least squares to the theoretical model to four of the larges US states to provide empirical results and examine differences in behavior across the regions.

The main conclusions from the paper are as follows. First, our results highlight the substantial influence of public interest, or the "fear factor," in shaping individual behavior during the pandemic. This factor emerges as a formidable driver of behavior, rivaling the impact of formal stringency measures in shaping public responses. This result implies that news effects can have as significant impact on individual behavior as policy in managing the negative health and economic outcomes of pandemics. Second, there is also a nonlinear reaction of mobility on policy, but in interesting ways. We find that as stringency rises, California residents initially increase their level of mobility and need more stringency to induce them to reduce moving around. This is contrary to the other three states in the sample, all of which show that stringency reduces movement but at a decreasing rate, that is there are diminishing returns to greater stringency. Third, we are able to demonstrate that there is some degree of exogeneity with respect to how policy is conducted. Our result corroborate those found in Sonora (2022), who demonstrates there is a trade-off between resident health and the state economy and that this trade-off can vary considerably across states. The exogeneity of policy also aligns with the results found in Sonora and Gottwald-Belinić (2023) which assumed exogenous policy to determine whether or not policy has an impact on resident behavior. Results from our model, which allows policy-makers to be influenced by resident behavior, suggest that COVID policy was partially exogenous in the states in our sample, that is mobility has a positive or zero effect on stringency index.

However, we also find that vaccination rates, another indicator of resident preferences, do impact stringency measures. It is interesting to note that higher vaccination rates has a strong influence on policy-makers to reduce restrictions on mobility. This suggests that policy-makers are aware of the unpopularity of stringency and are quick to reduce restrictions if residents "voluntarily" reduce the probability contracting the disease through higher vaccination rates. This observation arises from the fact that vaccination robustly reduces spread of pandemics even in periods of high mobility which is a robust predictor for contagion.

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Tables

Table 1: Descriptive statistics

		count	mean	sd	min	max
SI	CA	105	3.86	0.45	2.12	4.41
	FL	104	3.66	0.48	1.72	4.41
	NY	105	3.89	0.48	2.12	4.41
	TX	105	3.68	0.57	1.02	4.36
GMI	CA	105	-18.68	5.60	-31.51	2.37
	FL	105	-14.73	6.57	-32.49	3.20
	NY	105	-18.50	7.30	-38.17	2.69
	TX	105	-11.25	5.84	-28.94	4.69
$\Delta Case$	CA	104	0.12	0.29	0.002	1.70
	FL	102	0.15	0.40	0.002	2.54
	NY	102	0.15	0.62	0.001	5.02
	TX	101	0.13	0.32	0.003	2.17
$\Delta Death$	CA	101	0.12	0.28	-0.0022	1.85
	FL	101	0.10	0.25	0.0003	1.55
	NY	100	0.08	0.34	0.0006	2.61
	TX	100	0.11	0.28	0.0030	2.08
UR	CA	105	7.07	5.64	2.04	27.75
	TX	105	3.78	3.32	0 .85	11.39
	NY	105	6.84	6.15	1.69	23.43
	FL	105	2.79	3.56	0.37	25.04

Table 2: Correlation matrix

CA

	si_CA	gmi_CA	dc_CA	u_CA	v_CA	gs_CA	ec_CA
si_CA	1.0						
gmi_CA	-0.8	1.0					
dc_CA	0.1	0.0	1.0				
u_CA	0.6	-0.5	0.1	1.0			
v_CA	-0.7	0.4	-0.3	-0.6	1.0		
gs_CA	0.4	-0.6	-0.1	-0.0	0.0	1.0	
ec_CA	-0.7	0.6	-0.2	-0.9	0.8	-0.1	1.0

NY

	si_NY	gmi_NY	dc_NY	u_NY	v_NY	gs_NY	ec_NY
si_NY	1.0						
gmi_NY	-0.7	1.0					
dc_NY	0.0	0.1	1.0				
u_NY	0.7	-0.6	-0.0	1.0			
v_NY	-1.0	0.6	-0.2	-0.6	1.0		
gs_NY	0.2	-0.4	-0.0	-0.1	-0.2	1.0	
ec_NY	-0.8	0.8	-0.1	-0.9	0.8	-0.1	1.0

FL

	si_FL	gmi_FL	dc_FL	u_FL	v_FL	gs_FL	ec_FL
si_FL	1.0						
gmi_FL	-0.8	1.0					
dc_FL	0.3	-0.1	1.0				
u_FL	0.7	-0.6	0.0	1.0			
v_FL	-0.8	0.7	-0.3	-0.5	1.0		
gs_FL	0.2	-0.2	0.1	-0.0	-0.1	1.0	
ec_FL	-0.9	0.8	-0.2	-0.8	0.8	-0.1	1.0

TX

	si_TX	gmi_TX	dc_TX	u_TX	v_TX	gs_TX	ec_TX
si_TX	1.0						
gmi_TX	-0.7	1.0					
dc_TX	0.4	-0.4	1.0				
u_TX	0.7	-0.6	0.2	1.0			
v_TX	-0.9	0.7	-0.3	-0.7	1.0		
gs_TX	0.1	-0.3	0.3	0.1	-0.2	1.0	
ec_TX	-0.8	0.8	-0.3	-0.9	0.9	-0.2	1.0

Table 3: Comparison of the model estimates for CA, NY, FL, TX - cases

	(1)
	si_CA
si_CA	
L.si_CA	0.670***
	(0.000)
L.dc_CA	0.149***
	(0.001)
u_CA	-0.024***
	(0.000)
L.u_CA	0.016***
	(0.001)
L.gmi_CA	-0.001
	(0.750)
L.v_CA	-0.004***
	(0.000)
L.beds_CA	-0.344*
	(0.060)
gmi_CA	
L.gmi_CA	0.646***
	(0.000)
L.dc_CA	-5.784***
	(0.000)
L.si_CA	-47.708***
	(0.000)
L.sqsi_CA	6.240***
	(0.000)
L.u_CA	0.014
	(0.692)
L.v_CA	0.026**
	(0.029)
L.gs_CA	-1.106**
	(0.014)
dc_CA	
L.dc_CA	0.798***
	(0.000)
L.gmi_CA	0.015***
	(0.000)
L.u_CA	-0.003
	(0.297)
L.giv_CA	0.000***
	(0.000)
L.v_CA	-0.009***
	(0.000)
L.gs_CA	-0.034
	(0.167)
L.seas1	-0.019
	(0.345)
L.biden	-0.056*
	(0.075)
u_CA	
L.u_CA	0.686***
	(0.000)
L.gmi_CA	0.016
	(0.817)
L.si_CA	1.128
	(0.282)
L.ec_CA	-0.244**
	(0.018)
N	102

p-values in parentheses
* p<.10, ** p<.05, *** p<.01

	(1)
	si_NY
si_NY	
L.si_NY	0.682***
	(0.000)
L.dc_NY	-0.029
	(0.543)
u_NY	0.093***
	(0.001)
L.u_NY	-0.087***
	(0.001)
L.gmi_NY	0.008***
	(0.000)
L.v_NY	-0.004***
	(0.001)
L.beds_NY	-0.340
	(0.178)
gmi_NY	
L.gmi_NY	0.580***
	(0.000)
L.dc_NY	-3.793***
	(0.000)
L.si_NY	40.240**
	(0.022)
L.sqsi_NY	-5.480**
	(0.025)
L.u_NY	-0.032
	(0.561)
L.v_NY	0.013
	(0.730)
L.gs_NY	-2.456***
	(0.000)
dc_NY	
L.dc_NY	0.708***
	(0.000)
L.gmi_NY	0.021***
	(0.000)
L.u_NY	0.006
	(0.213)
L.giv_NY	0.000***
	(0.004)
L.v_NY	-0.007***
	(0.001)
L.gs_NY	0.061
	(0.205)
L.seas1	-0.061*
	(0.089)
L.biden	-0.012
	(0.819)
u_NY	
L.u_NY	0.927***
	(0.000)
L.gmi_NY	-0.087***
	(0.001)
L.si_NY	-0.179
	(0.669)
L.ec_NY	-0.017
	(0.707)
N	100

p-values in parentheses
* p<.10, ** p<.05, *** p<.01

	(1)
	si_FL
si_FL	
L.si_FL	0.509***
	(0.000)
L.dc_FL	0.170***
	(0.000)
u_FL	0.084***
	(0.000)
L.u_FL	-0.027***
	(0.000)
L.gmi_FL	0.009**
	(0.023)
L.v_FL	-0.004***
	(0.000)
L.beds_FL	0.224*
	(0.079)
gmi_FL	
L.gmi_FL	0.685***
	(0.000)
L.dc_FL	-4.521***
	(0.000)
L.si_FL	21.569
	(0.128)
L.sqsi_FL	-2.848
	(0.126)
L.u_FL	0.031
	(0.635)
L.v_FL	0.049***
	(0.006)
L.gs_FL	-0.201
	(0.549)
dc_FL	
L.dc_FL	0.728***
	(0.000)
L.gmi_FL	0.011***
	(0.000)
L.u_FL	0.005***
	(0.001)
L.giv_FL	0.000**
	(0.015)
L.v_FL	-0.002***
	(0.005)
L.gs_FL	0.012
	(0.239)
L.seas1	0.009
	(0.326)
L.biden	-0.073***
	(0.000)
u_FL	
L.u_FL	0.439***
	(0.000)
L.gmi_FL	-0.114*
	(0.080)
L.si_FL	1.711*
	(0.084)
L.ec_FL	-0.049
	(0.551)
N	100

p-values in parentheses
* p<.10, ** p<.05, *** p<.01

	(1)
	si_TX
si_TX	
L.si_TX	0.861***
	(0.000)
L.dc_TX	-0.005
	(0.944)
u_TX	0.164**
	(0.015)
L.u_TX	-0.154**
	(0.016)
L.gmi_TX	0.003
	(0.196)
L.v_TX	-0.003***
	(0.004)
L.beds_TX	0.701**
	(0.045)
gmi_TX	
L.gmi_TX	0.310***
	(0.001)
L.dc_TX	-3.762***
	(0.000)
L.si_TX	50.820***
	(0.005)
L.sqsi_TX	-7.232***
	(0.005)
L.u_TX	0.170
	(0.107)
L.v_TX	0.073***
	(0.004)
L.gs_TX	-1.400***
	(0.010)
dc_TX	
L.dc_TX	0.789***
	(0.000)
L.gmi_TX	0.014***
	(0.000)
L.u_TX	0.002
	(0.694)
L.giv_TX	0.000***
	(0.009)
L.v_TX	-0.004***
	(0.002)
L.gs_TX	0.003
	(0.889)
L.seas1	-0.011
	(0.602)
L.biden	-0.045
	(0.193)
u_TX	
L.u_TX	0.941***
	(0.000)
L.gmi_TX	-0.035**
	(0.028)
L.si_TX	0.256
	(0.322)
L.ec_TX	0.004
	(0.917)
N	100

p-values in parentheses
* p<.10, ** p<.05, *** p<.01

Table 4: Comparison of the model estimates for CA, NY, FL, TX - deaths

	(1)
	si_CA
si_CA	
L.si_CA	0.753***
	(0.000)
L.dd_CA	0.057*
	(0.097)
u_CA	-0.012**
	(0.010)
L.u_CA	0.008**
	(0.038)
L.gmi_CA	-0.002
	(0.449)
L.v_CA	-0.003***
	(0.000)
L.beds_CA	-0.085
	(0.676)
gmi_CA	
L.gmi_CA	0.501***
	(0.000)
L.dd_CA	-4.865***
	(0.000)
L.si_CA	-10.301
	(0.681)
L.sqsi_CA	1.407
	(0.676)
L.u_CA	0.020
	(0.638)
L.v_CA	0.046***
	(0.001)
L.gs_CA	-1.631***
	(0.000)
dd_CA	
L.dd_CA	0.892***
	(0.000)
L.gmi_CA	0.020***
	(0.000)
L.u_CA	-0.001
	(0.752)
L.giv_CA	0.000***
	(0.003)
L.v_CA	-0.007***
	(0.000)
L.gs_CA	0.031
	(0.160)
L.seas1	-0.014
	(0.398)
L.biden	-0.010
	(0.689)
u_CA	
L.u_CA	0.654***
	(0.000)
L.gmi_CA	0.032
	(0.726)
L.si_CA	0.710
	(0.513)
L.ec_CA	-0.318**
	(0.010)
N	100

p-values in parentheses
* p<.10, ** p<.05, *** p<.01

	(1)
	si_NY
si_NY	
L.si_NY	0.718***
	(0.000)
L.dd_NY	-0.054
	(0.183)
u_NY	0.099***
	(0.000)
L.u_NY	-0.094***
	(0.000)
L.gmi_NY	0.008***
	(0.000)
L.v_NY	-0.004***
	(0.003)
L.beds_NY	-0.331
	(0.115)
gmi_NY	
L.gmi_NY	0.662***
	(0.000)
L.dd_NY	-1.974***
	(0.002)
L.si_NY	38.205**
	(0.019)
L.sqsi_NY	-5.558**
	(0.015)
L.u_NY	-0.007
	(0.891)
L.v_NY	-0.029
	(0.466)
L.gs_NY	-2.364***
	(0.000)
dd_NY	
L.dd_NY	0.666***
	(0.000)
L.gmi_NY	0.003***
	(0.001)
L.u_NY	0.000
	(0.858)
L.giv_NY	0.000
	(0.128)
L.v_NY	-0.001*
	(0.051)
L.gs_NY	0.007
	(0.333)
L.seas1	-0.005
	(0.461)
L.biden	0.001
	(0.892)
u_NY	
L.u_NY	0.937***
	(0.000)
L.gmi_NY	-0.104***
	(0.000)
L.si_NY	-0.518
	(0.168)
L.ec_NY	-0.016
	(0.703)
N	99

p-values in parentheses
* p<.10, ** p<.05, *** p<.01

	(1)
	si_FL
si_FL	
L.si_FL	0.515***
	(0.000)
L.dd_FL	0.307***
	(0.000)
u_FL	0.078***
	(0.000)
L.u_FL	-0.021***
	(0.001)
L.gmi_FL	0.016***
	(0.000)
L.v_FL	-0.004***
	(0.000)
L.beds_FL	0.186
	(0.124)
gmi_FL	
L.gmi_FL	0.481***
	(0.000)
L.dd_FL	-6.316***
	(0.000)
L.si_FL	39.074***
	(0.009)
L.sqsi_FL	-5.170***
	(0.008)
L.u_FL	0.023
	(0.763)
L.v_FL	0.083***
	(0.000)
L.gs_FL	-0.508
	(0.169)
dd_FL	
L.dd_FL	1.036***
	(0.000)
L.gmi_FL	0.021***
	(0.000)
L.u_FL	0.004*
	(0.076)
L.giv_FL	0.000***
	(0.000)
L.v_FL	-0.005***
	(0.000)
L.gs_FL	0.002
	(0.874)
L.seas1	-0.000
	(0.990)
L.biden	-0.102***
	(0.000)
u_FL	
L.u_FL	0.405***
	(0.000)
L.gmi_FL	-0.090
	(0.173)
L.si_FL	1.220
	(0.225)
L.ec_FL	-0.134
	(0.105)
N	100

p-values in parentheses
* p<.10, ** p<.05, *** p<.01

	(1)
	si_TX
si_TX	
L.si_TX	0.877***
	(0.000)
L.dd_TX	0.016
	(0.794)
u_TX	0.161***
	(0.008)
L.u_TX	-0.151***
	(0.009)
L.gmi_TX	0.003
	(0.226)
L.v_TX	-0.002***
	(0.007)
L.beds_TX	0.812**
	(0.014)
gmi_TX	
L.gmi_TX	0.311***
	(0.001)
L.dd_TX	-3.629***
	(0.000)
L.si_TX	46.519**
	(0.010)
L.sqsi_TX	-6.554**
	(0.010)
L.u_TX	0.126
	(0.240)
L.v_TX	0.077***
	(0.004)
L.gs_TX	-1.520***
	(0.004)
dd_TX	
L.dd_TX	0.692***
	(0.000)
L.gmi_TX	0.002**
	(0.034)
L.u_TX	0.001
	(0.438)
L.giv_TX	0.000
	(0.251)
L.v_TX	-0.001
	(0.135)
L.gs_TX	0.010
	(0.104)
L.seas1	0.010
	(0.140)
L.biden	-0.016
	(0.124)
u_TX	
L.u_TX	0.960***
	(0.000)
L.gmi_TX	-0.049***
	(0.001)
L.si_TX	0.078
	(0.744)
L.ec_TX	0.017
	(0.601)
N	99

p-values in parentheses
* p<.10, ** p<.05, *** p<.01

Table 5: Comparison of the threshold model estimates for CA, NY, FL, TX

	(1)
	si_CA
si_CA	
L.si_CA	0.712***
	(0.000)
L.dc_CA	0.233***
	(0.000)
u_CA	-0.026**
	(0.011)
L.u_CA	0.020**
	(0.019)
L.gmi_CA	0.001
	(0.865)
L.v_CA	-0.004***
	(0.000)
gmi_CA	
L.gmi_CA	0.567***
	(0.000)
L.dc_CA	-4.629***
	(0.000)
L.upsi_CA	-2.791***
	(0.000)
L.downsi_CA	-2.964***
	(0.000)
L.u_CA	0.043
	(0.237)
L.v_CA	0.002
	(0.807)
L.gs_CA	-1.778***
	(0.000)
dc_CA	
L.dc_CA	0.807***
	(0.000)
L.gmi_CA	0.015***
	(0.000)
L.u_CA	-0.002
	(0.223)
L.giv_CA	0.001***
	(0.000)
L.v_CA	-0.011***
	(0.000)
L.gs_CA	-0.060***
	(0.006)
u_CA	
L.u_CA	0.820***
	(0.000)
L.gmi_CA	0.007
	(0.919)
L.si_CA	1.931*
	(0.055)
N	103

p-values in parentheses
* p<.10, ** p<.05, *** p<.01

	(1)
	si_NY
si_NY	
L.si_NY	0.815***
	(0.000)
L.dc_NY	0.135**
	(0.011)
u_NY	-0.070*
	(0.063)
L.u_NY	0.068*
	(0.054)
L.gmi_NY	-0.002
	(0.463)
L.v_NY	-0.002
	(0.287)
gmi_NY	
L.gmi_NY	0.662***
	(0.000)
L.dc_NY	-2.754***
	(0.000)
L.upsi_NY	-1.752
	(0.440)
L.downsi_NY	-1.860
	(0.415)
L.u_NY	-0.078
	(0.139)
L.v_NY	-0.002
	(0.955)
L.gs_NY	-3.191***
	(0.000)
dc_NY	
L.dc_NY	0.473***
	(0.000)
L.gmi_NY	0.008*
	(0.063)
L.u_NY	0.000
	(0.979)
L.giv_NY	0.000
	(0.108)
L.v_NY	-0.005*
	(0.050)
L.gs_NY	0.081
	(0.148)
u_NY	
L.u_NY	0.943***
	(0.000)
L.gmi_NY	-0.072***
	(0.001)
L.si_NY	-0.134
	(0.737)
N	101

p-values in parentheses
* p<.10, ** p<.05, *** p<.01

	(1)
	si_FL
si_FL	
L.si_FL	0.412***
	(0.000)
L.dc_FL	0.208***
	(0.000)
u_FL	0.082***
	(0.000)
L.u_FL	-0.022***
	(0.008)
L.gmi_FL	0.013***
	(0.002)
L.v_FL	-0.005***
	(0.000)
gmi_FL	
L.gmi_FL	0.765***
	(0.000)
L.dc_FL	-4.187***
	(0.000)
L.upsi_FL	-0.519
	(0.537)
L.downsi_FL	-0.375
	(0.665)
L.u_FL	0.002
	(0.977)
L.v_FL	0.020*
	(0.054)
L.gs_FL	-0.263
	(0.435)
dc_FL	
L.dc_FL	0.831***
	(0.000)
L.gmi_FL	0.018***
	(0.000)
L.u_FL	0.008***
	(0.003)
L.giv_FL	0.000***
	(0.003)
L.v_FL	-0.006***
	(0.000)
L.gs_FL	-0.034*
	(0.055)
u_FL	
L.u_FL	0.427***
	(0.000)
L.gmi_FL	-0.066
	(0.261)
L.si_FL	3.036***
	(0.001)
N	101

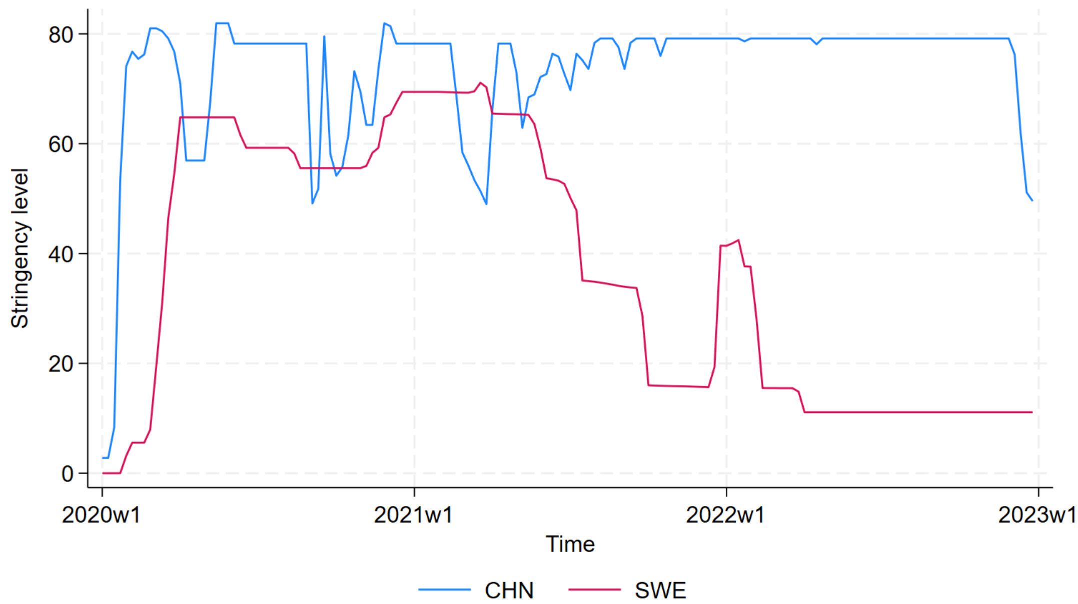
p-values in parentheses
* p<.10, ** p<.05, *** p<.01

	(1)
	si_TX
si_TX	
L.si_TX	0.840***
	(0.000)
L.dc_TX	0.067
	(0.598)
u_TX	0.049
	(0.644)
L.u_TX	-0.048
	(0.638)
L.gmi_TX	0.003
	(0.305)
L.v_TX	-0.003**
	(0.031)
gmi_TX	
L.gmi_TX	0.482***
	(0.000)
L.dc_TX	-4.655***
	(0.000)
L.upsi_TX	-0.264
	(0.876)
L.downsi_TX	-0.304
	(0.860)
L.u_TX	0.047
	(0.641)
L.v_TX	0.061**
	(0.020)
L.gs_TX	-1.512***
	(0.007)
dc_TX	
L.dc_TX	0.801***
	(0.000)
L.gmi_TX	0.013***
	(0.000)
L.u_TX	0.003
	(0.350)
L.giv_TX	0.000***
	(0.009)
L.v_TX	-0.005***
	(0.000)
L.gs_TX	-0.000
	(0.993)
u_TX	
L.u_TX	0.939***
	(0.000)
L.gmi_TX	-0.034**
	(0.016)
L.si_TX	0.244
	(0.295)
N	100

p-values in parentheses
* p<.10, ** p<.05, *** p<.01

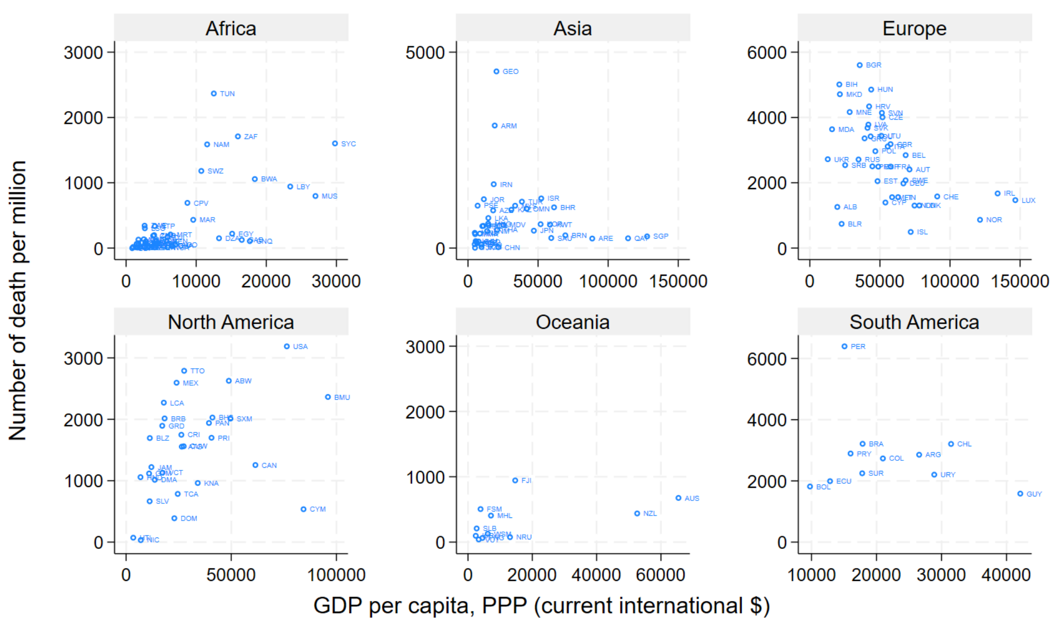
Figures

Figure 4: Stringency index in China and Sweden



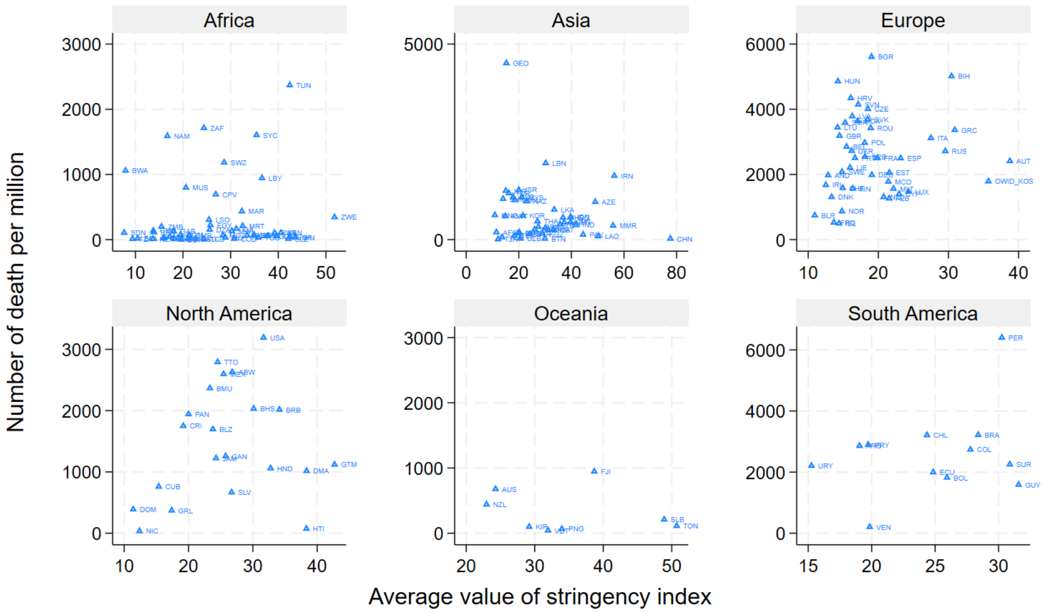
Source: Hale et al. (2021)

Figure 5: Correlation between GDP per capita and number of death per million



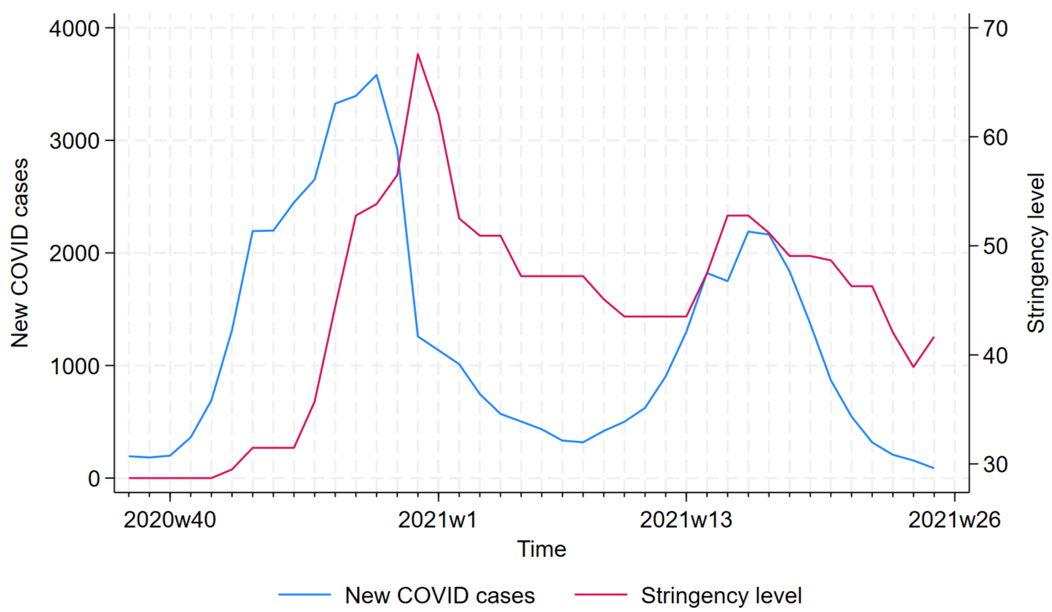
Source: Hale et al. (2021); World Bank

Figure 6: Correlation between average stringency index and number of death per million



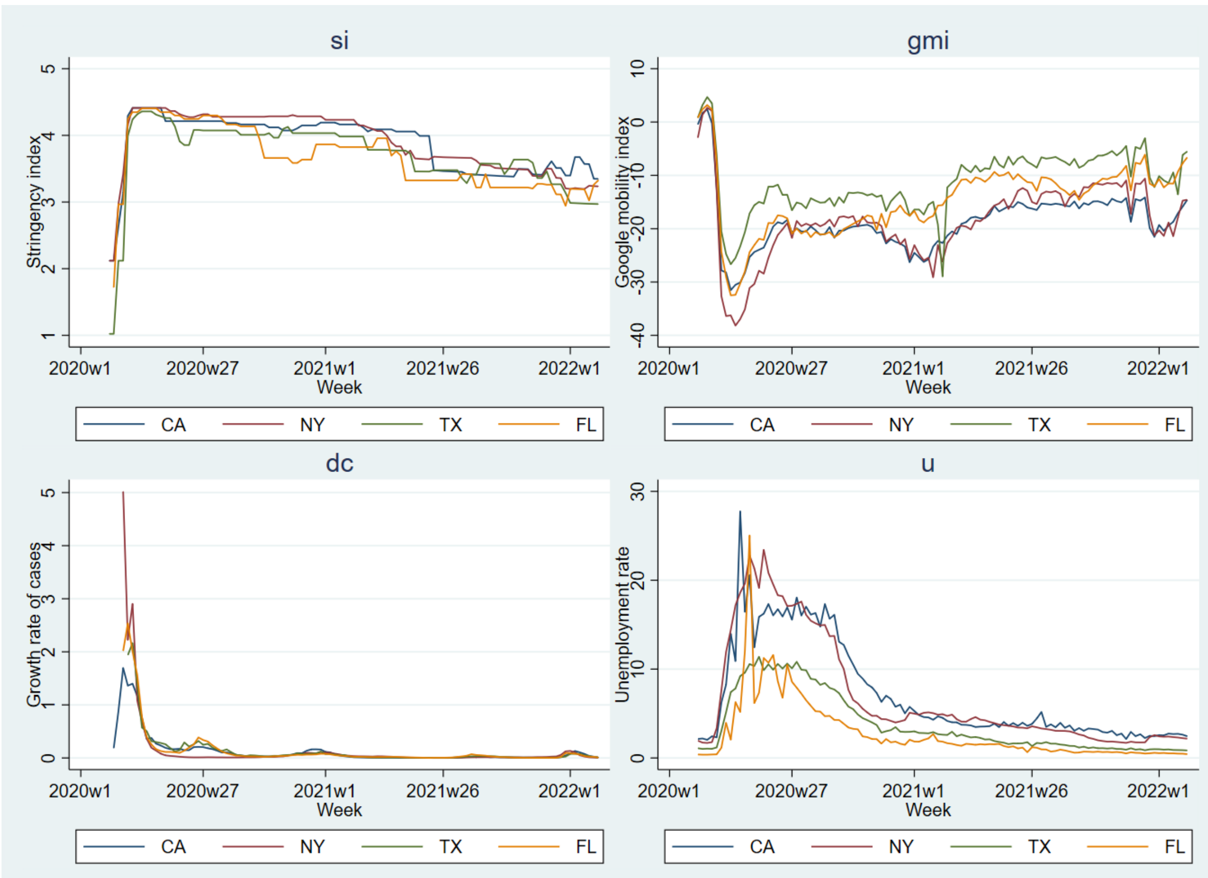
Source: Hale et al. (2021); World Bank

Figure 7: Stringency index and number of new cases in Croatia (December 2020-June 2021)



Source: Hale et al. (2021)

Figure 8: Data on endogenous variables



Source: Hale et al. (2021)

Figure 9: Nonlinear relationship between *si* and *gmi* for Table 3

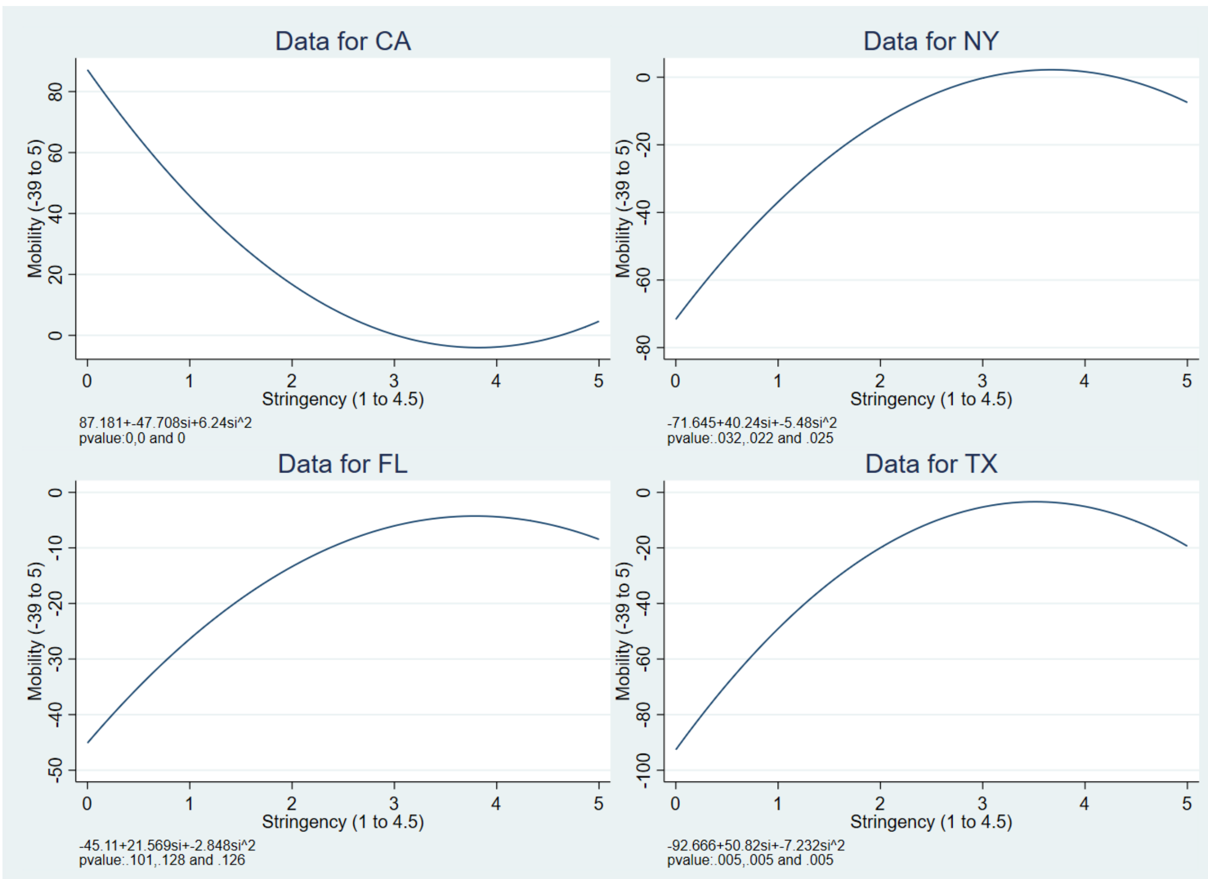
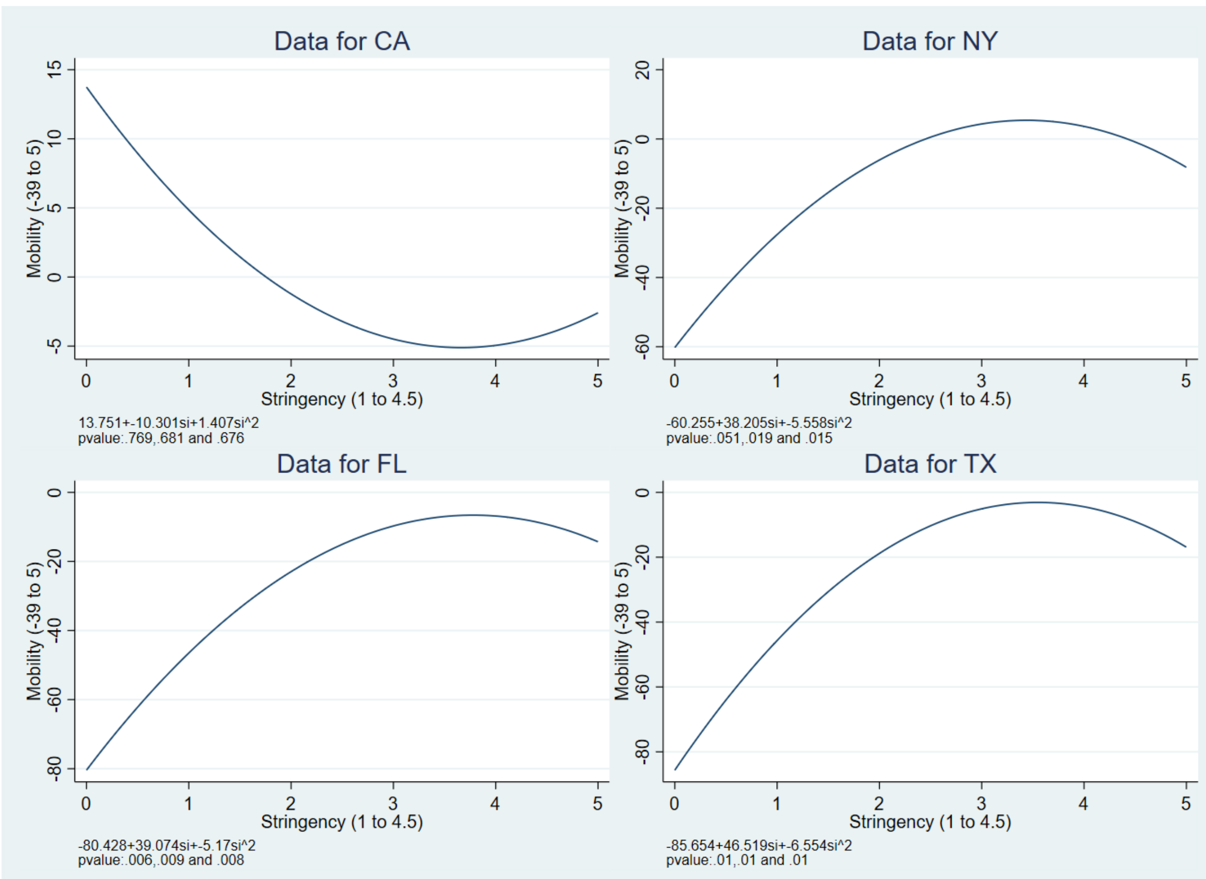


Figure 10: Nonlinear relationship between *si* and *gmi* in the model without news effect - Table 4



Appendix A. Derivation of the C-SI model

We present derivation of the C-SI model in two parts. First, we present the derivation of the equilibrium and after that we derive slopes and shifts of si and c curves.

Appendix A.1. Derivation of the equilibrium value

Matrix representation of the model defined in equation 2 through 5 is given in matrix notation of the form $Ax = B$, where A is matrix of coefficients, x is vector of endogenous variables and B is vector of exogenous variables:

$$\begin{pmatrix} -1 & \mathrm{si}_c & \mathrm{si}_{\mathrm{gmi}} & \mathrm{si}_u \\ 0 & -1 & c_{\mathrm{gmi}} & c_u \\ \mathrm{gmi}_{\mathrm{si}} & \mathrm{gmi}_c & -1 & \mathrm{gmi}_u \\ u_{\mathrm{si}} & 0 & u_{\mathrm{gmi}} & -1 \end{pmatrix} \begin{pmatrix} \mathrm{si} \\ c \\ \mathrm{gmi} \\ u \end{pmatrix} = \begin{pmatrix} -\mathrm{si}_v\, v \\ -c_{\mathrm{gs}}\, \mathrm{gs} - c_v\, v \\ -\mathrm{gmi}_{\mathrm{gs}}\, \mathrm{gs} - \mathrm{gmi}_v\, v \\ -\mathrm{ec}\, u_{\mathrm{ec}} \end{pmatrix} \tag{A.1}$$

In order to solve the 4×4 model for the **equilibrium** of the entire 4x4 system for the variable si we need to apply Cramer's rule and calculate determinant of the matrix:

$$A_j = \begin{pmatrix} -\mathrm{si}_v\, v & \mathrm{si}_c & \mathrm{si}_{\mathrm{gmi}} & \mathrm{si}_u \\ -c_{\mathrm{gs}}\, \mathrm{gs} - c_v\, v & -1 & c_{\mathrm{gmi}} & c_u \\ -\mathrm{gmi}_{\mathrm{gs}}\, \mathrm{gs} - \mathrm{gmi}_v\, v & \mathrm{gmi}_c & -1 & \mathrm{gmi}_u \\ -\mathrm{ec}\, u_{\mathrm{ec}} & 0 & u_{\mathrm{gmi}} & -1 \end{pmatrix} \tag{A.2}$$

in which first row is vector B from equation (A.1).

In the next step we need to calculate determinant of the matrix A from equation (A.1) and the solution for the **equilibrium** of the si equation will be:

$$si = |A_j|/|A| \tag{A.3}$$

In order to derive reduced form solutions for c, gmi and u, we can iterate Cramer's in order to calculate determinant $|A_j|$ for each variable. Reduced forms of equations for each variable can be used for simulations of shocks in vaccination rate v, news effects gs and economic conditions ec.

Besides simulations, the system of equation can be used in order to analyze shocks of exogenous variables within the two-dimensional diagram in the c and si space. That way we can get useful tool for the development of the intuition about the interplay of various policy tools, economic limitations and pandemic dynamics.

Appendix A.2. Shifts and slopes of si curve

With a goal to build two-dimensional model within c and si space, we proceed by deriving slopes and shifts of reduced forms of c and si equations from equation (A.1).

First, we start with si curve. In order to derive slope and shift of the si curve in the $c - si$ space we assume that c is exogenous. Therefore, A matrix and x and B vectors for si curve's shift and slope derivation are:

$$\begin{pmatrix} -1 & \mathrm{si}_{\mathrm{gmi}} & \mathrm{si}_u \\ \mathrm{gmi}_{\mathrm{si}} & -1 & \mathrm{gmi}_u \\ u_{\mathrm{si}} & u_{\mathrm{gmi}} & -1 \end{pmatrix} \begin{pmatrix} \mathrm{si} \\ \mathrm{gmi} \\ u \end{pmatrix} = \begin{pmatrix} -c\,\mathrm{si}_c - \mathrm{si}_v\, v \\ -c\,\mathrm{gmi}_c - \mathrm{gmi}_{\mathrm{gs}}\,\mathrm{gs} - \mathrm{gmi}_v\, v \\ -\mathrm{ec}\, u_{\mathrm{ec}} \end{pmatrix} \tag{A.4}$$

matrix A_j for si curve is:

$$A_j = \begin{pmatrix} -c\,\mathrm{si}_c - \mathrm{si}_v\, v & \mathrm{si}_{\mathrm{gmi}} & \mathrm{si}_u \\ -c\,\mathrm{gmi}_c - \mathrm{gmi}_{\mathrm{gs}}\,\mathrm{gs} - \mathrm{gmi}_v\, v & -1 & \mathrm{gmi}_u \\ -\mathrm{ec}\, u_{\mathrm{ec}} & u_{\mathrm{gmi}} & -1 \end{pmatrix} \tag{A.5}$$

In order to solve the model in equation (A.4) for si, we need to calculate determinant of the matrix A_j:

$$\begin{aligned} A_j =& c\,\mathrm{gmi}_u\,\mathrm{si}_c\, u_{\mathrm{gmi}} - \mathrm{si}_v\, v - c\,\mathrm{gmi}_c\,\mathrm{si}_{\mathrm{gmi}} - \mathrm{gmi}_{\mathrm{gs}}\,\mathrm{gs}\,\mathrm{si}_{\mathrm{gmi}} - \mathrm{ec}\,\mathrm{si}_u\, u_{\mathrm{ec}} - \mathrm{gmi}_v\,\mathrm{si}_{\mathrm{gmi}}\, v \\ & - c\,\mathrm{gmi}_c\,\mathrm{si}_u\, u_{\mathrm{gmi}} - c\,\mathrm{si}_c - \mathrm{ec}\,\mathrm{gmi}_u\,\mathrm{si}_{\mathrm{gmi}}\, u_{\mathrm{ec}} - \mathrm{gmi}_{\mathrm{gs}}\,\mathrm{gs}\,\mathrm{si}_u\, u_{\mathrm{gmi}} + \mathrm{gmi}_u\,\mathrm{si}_v\, u_{\mathrm{gmi}}\, v - \\ & \mathrm{gmi}_v\,\mathrm{si}_u\, u_{\mathrm{gmi}}\, v \end{aligned} \tag{A.6}$$

and determinant of the matrix A from equation (A.4):

$$|A| = \mathrm{gmi}_{\mathrm{si}}\,\mathrm{si}_{\mathrm{gmi}} + \mathrm{gmi}_u\, u_{\mathrm{gmi}} + \mathrm{si}_u\, u_{\mathrm{si}} + \mathrm{gmi}_{\mathrm{si}}\,\mathrm{si}_u\, u_{\mathrm{gmi}} + \mathrm{gmi}_u\,\mathrm{si}_{\mathrm{gmi}}\, u_{\mathrm{si}} - 1 \tag{A.7}$$

The ratio of equation (A.5) to equation (A.7) represents function of the si curve with c being exogenous:

$$si = |A_j|/|A| \tag{A.8}$$

In order to derive the **slope** of the *si* curve we need to take the partial derivation of the *si* curve with respect to c:

$$\partial si/\partial c = -\frac{\mathrm{si}_c + \mathrm{gmi}_c\,\mathrm{si}_{\mathrm{gmi}} + \mathrm{gmi}_c\,\mathrm{si}_u\,u_{\mathrm{gmi}} - \mathrm{gmi}_u\,\mathrm{si}_c\,u_{\mathrm{gmi}}}{\mathrm{gmi}_{\mathrm{si}}\,\mathrm{si}_{\mathrm{gmi}} + \mathrm{gmi}_u\,u_{\mathrm{gmi}} + \mathrm{si}_u\,u_{\mathrm{si}} + \mathrm{gmi}_{\mathrm{si}}\,\mathrm{si}_u\,u_{\mathrm{gmi}} + \mathrm{gmi}_u\,\mathrm{si}_{\mathrm{gmi}}\,u_{\mathrm{si}} - 1} = -\frac{\Phi_{sic}}{\Omega_{si}} > 0 \tag{A.9}$$

We assume that slope of the *si* curve is upward sloping in the $c - si$ space due to the fact that increase in number of cases *ceteris paribus* induces policy-makers to impose new COVID measures. In terms of theoretical model, this implies opposite signs of Φ_{sic} and Ω_{si} (either $\Phi_{sic} > 0$ and $\Omega_{si} < 0$ or $\Phi_{sic} < 0$ and $\Omega_{si} > 0$).

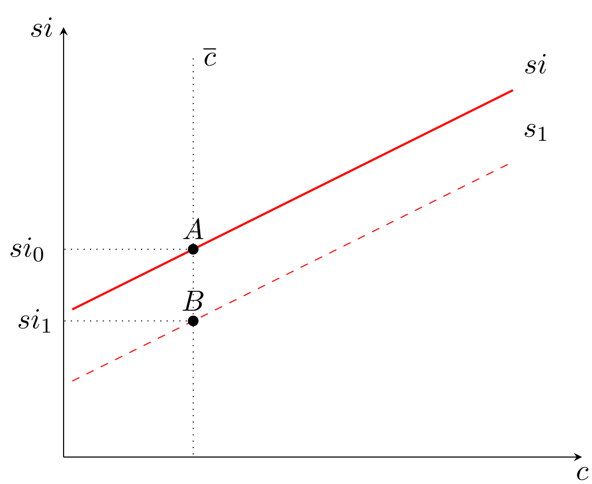
In the next step we proceed with derivation of the **shift** of the *si* curve. The partial derivation of the *si* function with respect to exogenous shock v is:

$$\partial si/\partial v = -\frac{\mathrm{si}_v + \mathrm{gmi}_v\,\mathrm{si}_{\mathrm{gmi}} - \mathrm{gmi}_u\,\mathrm{si}_v\,u_{\mathrm{gmi}} + \mathrm{gmi}_v\,\mathrm{si}_u\,u_{\mathrm{gmi}}}{\mathrm{gmi}_{\mathrm{si}}\,\mathrm{si}_{\mathrm{gmi}} + \mathrm{gmi}_u\,u_{\mathrm{gmi}} + \mathrm{si}_u\,u_{\mathrm{si}} + \mathrm{gmi}_{\mathrm{si}}\,\mathrm{si}_u\,u_{\mathrm{gmi}} + \mathrm{gmi}_u\,\mathrm{si}_{\mathrm{gmi}}\,u_{\mathrm{si}} - 1} = -\frac{\Phi_{siv}}{\Omega_{si}} < 0 \tag{A.10}$$

We assume that rise in vaccination rate will *ceteris paribus* decrease level of stringency for the given number of COVID cases. In terms of theoretical model, this implies that Φ_{siv} and Ω_{si} are of the same sign (either $\Phi_{siv} > 0$ and $\Omega_{si} > 0$ or $\Phi_{siv} < 0$ and $\Omega_{si} < 0$).

Following equation (A.9) and (A.10) Figure A.11 presents slope and the shift of the *si* curve due to rise in vaccination rate.

Figure A.11: Shift of the *si* curve in the $C - SI$ model



Appendix A.3. Shifts and slopes of the c curve

Once we have shift and slope of si function we can repeat procedure for the c curve. Now, si will be exogenous and c endogenous. Matrix A, vectors x and B for c curve are:

$$\begin{pmatrix} -1 & c_{\mathrm{gmi}} & c_u \\ \mathrm{gmi}_c & -1 & \mathrm{gmi}_u \\ 0 & u_{\mathrm{gmi}} & -1 \end{pmatrix} \begin{pmatrix} c \\ \mathrm{gmi} \\ u \end{pmatrix} = \begin{pmatrix} -c_{\mathrm{gs}}\,\mathrm{gs} - c_v\,v \\ -\mathrm{gmi}_{\mathrm{gs}}\,\mathrm{gs} - \mathrm{gmi}_{\mathrm{si}}\,\mathrm{si} - \mathrm{gmi}_v\,v \\ -\mathrm{ec}\,u_{\mathrm{ec}} - \mathrm{si}\,u_{\mathrm{si}} \end{pmatrix} \tag{A.11}$$

matrix A_j for c curve is:

$$A_j = \begin{pmatrix} -c_{\mathrm{gs}}\,\mathrm{gs} - c_v\,v & c_{\mathrm{gmi}} & c_u \\ -\mathrm{gmi}_{\mathrm{gs}}\,\mathrm{gs} - \mathrm{gmi}_{\mathrm{si}}\,\mathrm{si} - \mathrm{gmi}_v\,v & -1 & \mathrm{gmi}_u \\ -\mathrm{ec}\,u_{\mathrm{ec}} - \mathrm{si}\,u_{\mathrm{si}} & u_{\mathrm{gmi}} & -1 \end{pmatrix} \tag{A.12}$$

determinant of the matrix A_j in equation A.12 is:

$$\begin{aligned} |A_j| =& c_{\mathrm{gs}}\,\mathrm{gmi}_u\,\mathrm{gs}\,u_{\mathrm{gmi}} - c_v\,v - c_{\mathrm{gmi}}\,\mathrm{gmi}_{\mathrm{gs}}\,\mathrm{gs} - c_u\,\mathrm{ec}\,u_{\mathrm{ec}} - c_{\mathrm{gmi}}\,\mathrm{gmi}_{\mathrm{si}}\,\mathrm{si} - c_{\mathrm{gmi}}\,\mathrm{gmi}_v\,v - c_u\,\mathrm{si}\,u_{\mathrm{si}} - \\ & c_{\mathrm{gmi}}\,\mathrm{ec}\,\mathrm{gmi}_u\,u_{\mathrm{ec}} - c_{\mathrm{gs}}\,\mathrm{gs} - c_u\,\mathrm{gmi}_{\mathrm{gs}}\,\mathrm{gs}\,u_{\mathrm{gmi}} - c_{\mathrm{gmi}}\,\mathrm{gmi}_u\,\mathrm{si}\,u_{\mathrm{si}} - c_u\,\mathrm{gmi}_{\mathrm{si}}\,\mathrm{si}\,u_{\mathrm{gmi}} - c_u\,\mathrm{gmi}_v\,u_{\mathrm{gmi}}\,v \\ & + c_v\,\mathrm{gmi}_u\,u_{\mathrm{gmi}}\,v \end{aligned} \tag{A.13}$$

and determinant of the matrix A from equation A.11:

$$|A| = c_{\mathrm{gmi}}\,\mathrm{gmi}_c + \mathrm{gmi}_u\,u_{\mathrm{gmi}} + c_u\,\mathrm{gmi}_c\,u_{\mathrm{gmi}} - 1 \tag{A.14}$$

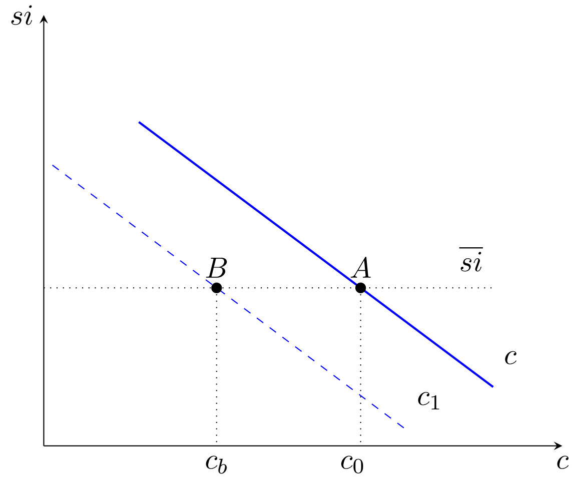
The ratio of equation A.13 to equation A.14 represents function of the c curve with si being exogenous:

$$c = |A_j|/|A| \tag{A.15}$$

In order to derive the **slope** of the c curve we need to take the partial derivation of the c curve with respect to si:

$$\partial c/\partial si = -\frac{c_{\mathrm{gmi}}\,\mathrm{gmi}_{\mathrm{si}} + c_u\,u_{\mathrm{si}} + c_{\mathrm{gmi}}\,\mathrm{gmi}_u\,u_{\mathrm{si}} + c_u\,\mathrm{gmi}_{\mathrm{si}}\,u_{\mathrm{gmi}}}{c_{\mathrm{gmi}}\,\mathrm{gmi}_c + \mathrm{gmi}_u\,u_{\mathrm{gmi}} + c_u\,\mathrm{gmi}_c\,u_{\mathrm{gmi}} - 1} = -\frac{\Phi_{csi}}{\Omega_c} < 0 \tag{A.16}$$

Figure A.12: Shift of the c curve in the $C - SI$ model



We assume that rise in stringency will *ceteris paribus* decrease number of cases. In terms of theoretical model, this implies downward slopping curve, meaning that Φ_{csi} and Ω_c are of the same sign (either $\Phi_{csi} > 0$ and $\Omega_c > 0$ or $\Phi_{csi} < 0$ and $\Omega_c < 0$).

Furthermore in order to derive **shift** of the c curve we take partial derivation of the c function with respect to exogenous shock v:

$$\partial c/\partial v = -\frac{c_v + c_{\text{gmi}}\,\text{gmi}_v + c_u\,\text{gmi}_v\,u_{\text{gmi}} - c_v\,\text{gmi}_u\,u_{\text{gmi}}}{c_{\text{gmi}}\,\text{gmi}_c + \text{gmi}_u\,u_{\text{gmi}} + c_u\,\text{gmi}_c\,u_{\text{gmi}} - 1} = -\frac{\Phi_{cv}}{\Omega_c} < 0 \tag{A.17}$$

We assume that rise in vaccination rate *ceterus paribus* decreases number of COVID cases. In terms of theoretical model, this implies that Φ_{cv} and Ω_c are of the same sign (either $\Phi_{cv} > 0$ and $\Omega_c > 0$ or $\Phi_{cv} < 0$ and $\Omega_c < 0$).

Based on derivation of the slope and shift in equation (A.16) and (A.17), Figure A.12 presents slope of the c curve and it's shift to the left due to increase in vaccination rate.

Appendix B. Derivation of the SI-MI model

Consider the following possibility, the "choice-state variable" model. We can choose SI and MI, policy and mobility. Therefore, we have the following 2×2 **choice** model. In this 2 equation model, on the choice side unemployment and cases are exogenous and will be analyzed in the "state" equations.

$$
\begin{aligned}
si &= si(\overset{(+)}{gmi}\,|\epsilon_s) && \text{(B.1)}\\
gmi &= gmi(\overset{(-)}{si}\,|\epsilon_g) && \text{(B.2)}
\end{aligned}
$$

and the 2×2 **state** variable model

$$
\begin{aligned}
c &= c(\overset{(+)}{u}\,|\nu_c) && \text{(B.3)}\\
u &= u(\overset{(+)}{c}\,|\nu_u) && \text{(B.4)}
\end{aligned}
$$

where $\epsilon = (c, u, vax, news)'$ and $\nu = (si, gmi, vax, news)'$. I'm rethinking how we label things, Ω refers to information, i.e. google searches.[6]

The total derivative of (B.1) and (B.2) are

$$
\begin{aligned}
dsi - si_{gmi}dgmi &= d\epsilon_{si} && \text{(B.5)}\\
dgmi - gmi_{si}dsi &= d\epsilon_g && \text{(B.6)}
\end{aligned}
$$

Equation (B.5) is the *policy "reaction"* function, P, and (B.6) is the *behavior* function, B. Not the policy function is positively related to cases, so if cases decrease the policy is becomes less restrictive (shifts down??? SI is on the vertical axis), $P \to P'$, and there is a new target level of mobility, similarly if the number of vaccinations increase. Alternatively, if we have two states, the one with the least stringiest policy has the greatest mobility.

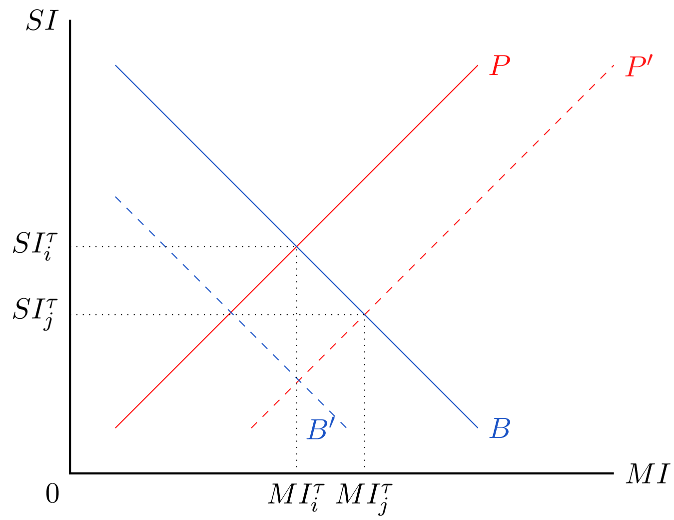
So now we have the $SI - GMI$ model, graphically this is

This would have the added bonus of *greatly* simplifying the $Ax = b$ and accompanying Cramer rule calculations.

$$
\underbrace{\begin{bmatrix} 1 & -s_g \\ -g_s & 1 \end{bmatrix}}_{A} \begin{bmatrix} ds \\ dg \end{bmatrix} = \begin{bmatrix} s_c dc + s_u du + s_v dv + s_\Omega d\Omega + d\upsilon_s \\ g_c dc + g_u du + g_v dv + g_\Omega d\Omega + d\upsilon_g \end{bmatrix}
$$

[6]is $c_u < 0$?

Figure B.13: Choice equations



with the determinant of A

$$|A| = 1 - s_g g_s > 0.$$

Then using Cramer's rule to see the impact of cases on SI and MI we have, if all other shocks are zero

$$\underbrace{\begin{bmatrix} s_c & -s_g \\ g_c & 1 \end{bmatrix}}_{A_1'}$$

thus

$$\frac{ds}{dc} = \frac{s_c + g_c s_g}{|A|} = \frac{(+) + (-)(+)}{(+)} \gtrless 0?$$

however, if s_c, g_c and s_g are between (0,1) we can safely assume that $s_c > g_c s_g$.

We can also think of this being determined by the elasticity of policy to cases and mobility, i.e. the marginal rate of substitution between cases and mobility, which also represents attitudes towards risk,

$$\frac{s_c}{s_g} \gtrless g_c.$$

This say, if policy is relatively responsive to cases, they are risk averse, than the above would be positive. If policy-makers are risk takers, this *could be* negative. Depends on the policy-maker.

If the policy-makers is relatively risk averse,

$$\frac{ds}{dc} = \frac{s_c + g_c s_g}{|A|} > 0 \tag{B.7}$$

So if cases falls, the policy function moves to P' and the policy-maker allows more mobility, an downward shift in the policy function, $MI_i^\tau \to MI_j^\tau$. Next if we consider the effect of cases on mobility,

$$\underbrace{\begin{bmatrix} 1 & s_c \\ -g_s & g_c \end{bmatrix}}_{A_2'}$$

or

$$\frac{dg}{dc} = \frac{g_c + g_s s_c}{|A|} < 0 \tag{B.8}$$

a negative shift in the behavior function, say B' in the figure above. If people move around less, policy-makers can be reduce their restrictions, $SI_i^\tau \to SI_j^\tau$. We can do similar things for u and v.

From this we can also how effective policy is when trying to dictate mobility. If the B curve is inelastic, policy is ineffective compared to an elastic B curve. Similarly, the elasticity of the policy function dictates how responsive the policy-maker is to constituent preferences. In this case if the elasticity equals 1, then policy-makers have perfect insight into individual behavior.

Now let's focus on the state variables, cases and unemployment. From equations (B.3) and (B.4) we have

$$dc = c_u du + d\nu_c \tag{B.9}$$

$$du = u_c dc + d\nu_u \tag{B.10}$$

Which gives the slopes of the cases and unemployment curves, for the cases equation, curve C, we have

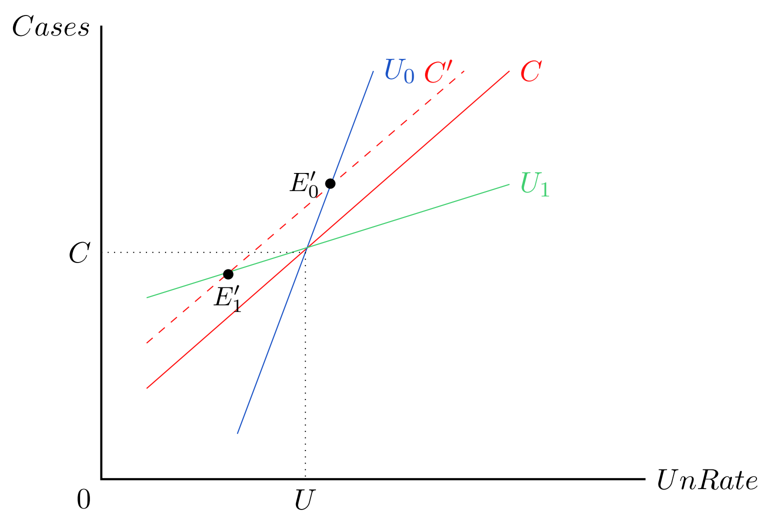
$$\frac{dc}{du} = c_u > 0$$

and for unemployment, curve U, we get

$$\frac{dc}{du} = \frac{1}{u_c} > 0$$

While both are positively sloped, if both u_c and c_u are less than one the U curve is *steeper* than the C curve. Graphically, we have

Figure B.14: State equations



A second case presents itself, if, on the other hand, $u_c > 1$ then we have the U_1 curve which could be shallower than the C curve which yields two possible equilibria if there is a shift in the C. If C shifts up, to say C', with the U_0 curve, both cases and unemployment increase, E'_0. However, with the U_1 the opposite occurs, at E'_1. [7] Also, because of the slopes of the U curves, we also get differences if they shift, if U_0 shifts right then U and C rise, and vice versa if U_1 shifts right.

Mathematically, the system of equations in (B.9) and (B.10) can be represented as

$$\underbrace{\begin{bmatrix} 1 & -c_u \\ -u_c & 1 \end{bmatrix}}_{B} \begin{bmatrix} dc \\ du \end{bmatrix} = \begin{bmatrix} c_s ds + c_g dg + c_v dv + c_\Omega d\Omega + d\xi_c \\ u_s ds + u_g dg + u_v dv + u_\Omega d\Omega + d\xi_u, \end{bmatrix}$$

[7] Note: if we used a system of differential equations, we could use a phase diagram to determine if one of the equilibria is stable and the other unstable.

the ξs represent other shocks to c and u, with the determinant of B

$$|B| = 1 - c_u u_c > 0.$$

if $c_u u_c < 1$, which we assume above. Assuming $dg = dv = d\Omega = d\xi_c = 0$ we can find how policy affects cases and unemployment, thus the matrix B is alternatively

$$\underbrace{\begin{bmatrix} c_s & -c_u \\ u_s & 1 \end{bmatrix}}_{B'}$$

and

$$\underbrace{\begin{bmatrix} 1 & c_s \\ -u_c & u_s \end{bmatrix}}_{B''}.$$

The effect of stringency on cases depends on the determinant of B' which is

$$\frac{dc}{ds} = \frac{\overbrace{c_s + c_u u_s}^{|B'|}}{|B|} = \frac{(-) + (+)(+)}{(+)} \gtreqless 0$$

depending on the marginal rate of substitution between u_s and c_s, if

$$\frac{u_s}{c_s} > c_u$$

then the above is negative, and vice versa. The effect of stringency on unemployment is

$$\frac{du}{ds} = \frac{u_s + u_c c_s}{|B|} = \frac{(+) + (+)(-)}{(+)} \gtreqless 0$$

again depending on the ratio of u_s/c_s. If this is greater than u_c, then the effect is negative, and positive otherwise. And repeat the exercise for mobility.