Assessing State Policy Responses to the COVID-19 Pandemic *

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ABSTRACT:

This paper demonstrates that moderate policy responses to the COVID-19 pandemic outperform both overly aggressive and overly permissive policies. To show this, we first quantify each American states' responsiveness using a structural model of pandemic response. The recovered responsiveness parameters allow us to simulate household policy-response behavior and compute consumption equivalent utility gains and losses (in consumption equivalent units) for both observed state policies and hypothetical national policies. We find that a limited government response is optimal in states with a small proportion of elderly households and that moderate national polices provide the highest level of welfare.

1 Introduction & Literature Review

In March of 2020 the Coronavirus pandemic spread rapidly through the United States, prompting an array of policy responses by US state governments. In order to control the propagation of the virus, states like Washington, California, and New York issued stay-at-home orders and restricted certain types of economic activity. The economic consequences of such policies were predictable: unemployment spiked upward, while consumption and national output contracted.

Yet these policies also affected the dynamics of viral propagation itself. With fewer interactions between individuals across the United States, the very parameters governing the evolution of infections changed. In this paper, we formulate a structural model of lockdown decisions that captures how these interventions interact with labor market conditions, household consumption and savings behavior, and the dynamics of infectious disease. We then use this structural model to evaluate the welfare implications of policy interventions.

The analysis presented in this paper constitutes two novel contributions to the pandemic response literature. First we recover the valuation of life implied by the sequence of policy decisions made in each US state. To do so, we propose a structural framework that allows for the estimation of this implied valuation in a panel of 39 US states. We begin by recovering a measure of viral propagation implied by each state's daily death count. To this end, we manipulate a standard Sick-Infected-Recovered-Dead (SIRD) model,a workhorse forecasting tool in the epidemiology literature. The recovered parameter yields a daily measure of the viral reproduction rate in each state across the duration of our panel.

Next, we formulate two projection models that a rational state government would utilize to forecast both unemployment rates and the values of our viral propagation parameter. We estimate both models using panel regression techniques. Weekly unemployment figures are obtained from the Bureau of Labor Statistics. The sequence of policy orders adopted by each state is then used to forecast expected unemployment rates and pandemic deaths across the first wave of the COVID-19 pandemic.

We then use the observed sequences of lockdown decisions to estimate a responsiveness parameter for each state. This parameter, which we denote governs the stringency with which each state imposes lockdown orders. In recovering this theoretical parameter, we conceive of state governments as rational actors who maximize societal welfare by weighing the trade-off between human life and economic activity. State governments are assumed to respond to weekly unemployment rates and death count, since measures of consumption are not available to policy makers on such short time horizon.

We use the responsiveness parameter, ω, to determine the relative value of life to employment in each state over the first wave of the COVID-19 pandemic. We find a wide range of implied life valuations. States that chose to implement only minimal restrictions for short periods of time, have low valuations. Idaho, for instance, has an implied life valuation of only 47 lives per job. In contrast, states that adopted stringent responses have much higher relative values of life; Washington state, for instance, has an implied life valuation of 792 lives per job.

Our second, and perhaps more significant, contribution is to assess the welfare implications of each state's policy response and to consider the consequences of a hypothetical national policy response. To conduct such assessments, we introduce a stylized dynamic model of household behavior. The model is similar in spirit to the seminal work of Ayagari (1991), in that households face an exogenous, idiosyncratic income process. In our formulation, households stochastically assume four distinct states: employed, unemployed, sick or dead. This model is empirically calibrated, using the results of section two, to determine the welfare gains and losses of each state's policy responses, in consumption equivalent units. These calculations are conducted relative to two baseline outcomes: a risk free scenario, in which there is no risk of infection or death, and a no mitigation scenario, in which state governments adopt no policy responses to the pandemic.

We consider both observed in-state polices and hypothetical national policies. The in-state evaluation yields welfare measures for observed outcomes, which are distorted by exogenous initial conditions. We find that almost all states adopted responses superior to total inaction, although states that overreacted or hesitated in implementing lockdown polices fared worse than if they had done nothing. States hit hardest at the onset of the pandemic – like New York and New Jersey – exhibited particularly hesitant responses. When they did responded to the virus, they found themselves with both high levels of infection and high levels of unemployment, the worst of both possible outcomes.

Relative to a no mitigation scenario, California, Georgia, and Colorado fared best. California is highly populous, and hence its no mitigation scenario produces a massive death count. As such, even the moderate, hesitant response of California's government induces large utility gains. A similar narrative explains the effectiveness of Georgia and Colorado – both have large, central metropolitan hubs that could induce disastrous death counts.

Our national evaluation procedure allows us to formulate a hypothetical national responses that is not distorted by initial conditions. That is, we formulate hypothetical responses when all states (and their associated responsiveness levels) face uniform levels of initial infections. In considering this national counterfactual we demonstrate that moderate lockdown policies produce higher levels of social welfare than both exceedingly lax restrictions and deeply prohibitive restrictions. That is, policies that were neither too restrictive nor too permissive are optimal. These policies correspond to the responses of states like Maryland and Arizona, where an effective initial lockdown was following by a gradual reopening.

Perhaps the most significant policy implication of this section is that overly lax responses tend to be less optimal than overly strict responses. This result is robust to a wide range of utility death penalties and to the inclusion of regional controls in our panel regressions, as we demonstrate in our final section.

The remainder of this paper is organized as follows: In section two we introduce a model of pandemic dynamics and then illustrate a method to recover model parameters from data. We then propose a representation of the policy decisions faced by state governments during the initial wave of COVID-19. We use both models to recover a measure of implied life valuation across states.

In section three, we develop a model of household response to the policy orders introduced by state governments. This environment, along with the results of section two, allow us to formulate utility theoretic evaluations of both states' observed policies and hypothetical national policies. In section four we summarize our findings and conclude. Section five contains the appendix, which includes robustness checks and plots of household consumption and savings responses.

1.1 Literature Review

Throughout 2020 and 2021 there has been a wealth of literature concerning pandemic response. Below we outline several novel contributions that have influenced the formulation of our analytical framework.

Eichenbaum et. al. (2020a) propose interacting a SIRD framework with economic models of household behavior to assess policy implications. Villaverde and Jones (2020) present a method for recovering dynamic parameters this a workhorse model of pandemic spread. The susceptible-infected-recovered-dead framework is a series of difference equations describing the evolution of a pandemic. The process outlined in this paper allows us to empirically determine values for the parameter governing new infections. In section 2 below we apply this method across a panel of states to establish an empirical measure of viral spread in each week of the first COVID-19 wave.

Rios-Rull et. al. (2020) posit a dynamic model with heterogeneous households and government transfers to assess the efficacy of lockdown policies. They find that the most severe restrictions are only optimal when vaccine distribution can occur relatively quickly. Otherwise, moderate lockdown polices are preferred according to their social welfare function.

This analysis – along with the seminal formulation of Ayagari (1994) – forms the basis of the household model presented in section 3, in that it includes old and young households who suffer differential infection and death risks. Our model differs in a number of key dimensions. Primarily, our model is more parsimonious and accordingly lends itself well to simulation using the results of section 2. Our conclusions broadly agree with their analysis – the most severe lockdown polices offer no welfare advantage over moderate policies. Similarly, a highly limited or even absent policy response shown to be suboptimal in out analysis.

Martin and Pindyck (2019) offer a method for calculating the welfare effects of catastrophes. Their framework posits a penalized utility function that accounts for the disutility of death. They suggest that this penalty should correspond to measure of the statistical value of life, and be set to 3-10 times a household's per-period income. In section 3 we use this approach and set a utility penalty of 5 times a household's income.

Several papers have attempted to assess the welfare implications of policy responses to COVID-19. Eichenbaum et. al. (2020b) demonstrate that economic outcomes absent any policy responses cannot be optimal,as households fail to internalize the effect their consumption and labour supply behavior has on infection rates. This conclusion conforms to out results in section three, where limited policy responses are shown to be sub-optimal.

Albanesi and Kim (2021) formulate a model of household response to the unique conditions imposed by COVID-19 lockdowns. Their framework examines the differential impact of lockdown policies on men and women, who occupy heterogeneous professions in varying proportions. They find that occupations characterized by inflexible working conditions and high public contact suffer most prominently from lockdown orders. Their analysis is similar to our paper in spirit, as it involves computing differential welfare effects for groups affected by the pandemic in different ways, although their model is more theoretical in nature.

Bognanni et. al. (2020) present a stylized model connecting pandemic spread and economic activity. They find that absent lockdown policy orders, a virulent disease would spread exponentially, prompting as endogenous reduction in economic activity as households attempt to reduce their risk of infection. Policy interventions such as lockdown orders and mask mandates improve upon this outcome in the event that a vaccine eventually halts the course of the pandemic. Governments have only a limited ability to affect welfare outcomes when the virus cannot be brought to heel through pharmaceutical means.

Their analysis is also similar to ours in spirit. However, Bognanni et. al. do not present the government as a rational decision making body. This addition is necessary in order to evaluate the efficiency of hypothetical national policies, which we present in section 3. Finally, Guerrieri et. al. (2020) analyze the welfare effects of the COVID-19 pandemic in a New Keynesian framework, specifically focusing on the persistent effects of the negative supply shock induced by policy responses. They find that targeted mitigation produces a first-best general equilibrium outcome.

None of the papers in the survey above attempt to empirically quantify the implicit life valuation of state governments or assess the welfare effects of state level policy responses. Similarly, none of these papers apply a structural decision model to assess the effects of national polices. Although we draw on both the empirical and theoretical contributions of the above analyses, our framework constitutes a novel approach to empirically assessing policy efficiency. We begin below with an outline of the first stage of the model.

2 Recovering Implied Life Valuations

Before we can begin to formulate a comprehensive, general model of pandemic response, we must first consider how an infectious disease spreads. Our analysis will rely heavily on Fernandez-Villaverde and Jones (2020), which posits an empirical strategy for recovering the parameters of a Susceptible-Infectious-Recovering-Dead (SIRD) model. Below we present an overview of their strategy before moving on to our implementation of this method and its results.

2.1 The SIRD Model

Consider an economy with N individuals. Let I_t represent the stock of infectious persons within an economy at time t. These are individuals that have the disease and can spread it through close contact with others. Let S_t be the stock of those susceptible. These are individual that have not contracted the disease, but could become infected. R_t is the stock of those recovering but who are no longer infectious. Finally, let D_t be the number of deceased, and C_t be the total number of recovered. Then,

$$S_t + I_t + R_t + D_t + C_t = N$$

Where N is the total population of the economy. The principal dynamics of the SIRD model are given as,

$$\begin{aligned}
\Delta S_{t+1} &= -\beta_t S_t I_t / N \\
\Delta I_{t+1} &= \beta_t S_t I_t / N - \gamma I_t \\
\Delta R_{t+1} &= \gamma I_t - \theta R_t \\
\Delta D_{t+1} &= \delta \theta R_t \\
\Delta C_{t+1} &= (1 - \delta) \theta R_t
\end{aligned}$$

Where $1/\gamma$ is the average number of days for which an afflicted individual is infectious, θ is the proportion of infectious leaving that state each period, and δ is the case fatality rate. Notice that all of these are biological parameters. Following Fernandez-Villaverde and Jones (2020), we use the values: $\gamma = .20$, $\theta = .10$, $\delta = .01$ throughout.

2.2 Recovering and Interpreting β_t

Let $d_{t+1} = D_{t+1} - D_t$ denote period recorded deaths. We use Δ to refer to the difference operator, and $\Delta\Delta$ to denote a difference of differences. Then the above system can be manipulated to obtain an analytical solution for β_t:

$$\beta_t = \frac{N}{S_t}(\gamma + \frac{\frac{1}{\theta}\Delta\Delta d_{t+3} + \Delta d_{t+2}}{\frac{1}{\theta}\Delta d_{t+1} + d_{t+1}}) \tag{1}$$

Using data from Johns Hopkins University, we formulate a panel data set tracking infections and deaths across 39 US states[1]. For each state we compute (1) from late January 2020 to September of the same year. This calculation yields the dynamic path of infection risk, β_t, in individual states over time. However, equation (1) is deceptively simple, and applying this calculation to actual data requires some additional manipulations.

First, our panel runs back to January 21st 2020, the date of the first recorded COVID-19 case in the United States. Since the first death from the virus was not recorded until nearly a month later, we drop 4 weeks of data from the panel. The resulting panel runs from mid February 2020 to January 2021, but will be further parsed out when we consider different estimation windows.

Second, the state time-series of daily deaths exhibit considerable variation. Often these data are not reported over weekends and holidays, leading to spikes in subsequent daily reports. To address this variation, we formulate our measure of deaths as a five day centered moving average of daily deaths in each state.

[1] Eleven states either do not have enough recorded deaths to meaningfully calculate values of β_t over time, or exhibit too much daily variation.

Similarly, deaths not exclusively caused by COVID-19 are not included in case counts. We therefore make an upward, multiplicative adjustment of 1.33 on each of our time-series. Both procedures are in line with those reported by Villaverde and Jones, and produce time series that exhibit limited volatility. Next, we apply a Hodrick-Prescott filter to isolate the trend component of each state's time-series of deaths. We apply this same filter to the double-difference components of equation (1). Absent this smoothing procedure, calculations of equation (1) yield wild fluctuations in β_t. Such fluctuations would complicate the estimation of our structural equations and are inherently unrealistic.

The values of β_t are calculated for each state in our sample. We consider a window of 16 weeks, both starting from five days before the first recorded death in each state. In appendix one below we present the dynamic paths of β_t for all selected states in our panel across the 16 week estimation window.

2.3 Relationship Between β_t and the Economy

The primary purpose of this model is to formulate a feedback mechanism between economic variables, state interventions, and the dynamics of infection. To this end, we first match each β_t^s time series with the dates for which lockdown orders are in effect. Notice that the superscript s here denotes geographic state.

Now, we think of state restrictions as taking on four discrete phases. These phases correspond to the phased plan adopted by the Washington State Department of Health in May 2020. In phase one, a stay-at-home order is active, accompanied by strict limitations on business activity. We classify states in phase one if such an order is active and retailers are allowed to operate at less than 25% capacity. In phase one restaurants are open only for take-out and delivery, while bars, dance-halls, and theatres are closed.

In phase two, restaurants and bars are open with capacity at or below 50%. Theatres, museums, gyms and non-essential retailers are open with strict capacity limits and social distancing. Phase three raises the capacity limits on eateries to over 50% and eases some restrictions on other types of enterprises, such as movie theatres. Phase four represents only the lightest of restrictions and no restaurant capacity limitations. For the sake of notational convenience, we set phase four as the base case.

We then consider the the linear projection of β^s_{t+1} on an indicator function $I(l)$, time and state dummies, along with regional controls. Here l is a categorical variable that represents the active lockdown phase. Formally, let $l_{s,t}$ be a vector of dummies indicating operative lockdown phase in state s at time t. Let α_s, α_R, and α_t denote state regional and time fixed effects respectively. The linear projection of spread parameter β on phase, state, region and time is given by,

$$\beta^s_{t+1} = \alpha_l(l_{s,t})' + \alpha_t \mathbb{1}(t) + \alpha_s \mathbb{1}(s) + \alpha_R \mathbb{1}(s) + \epsilon_{s,t} \tag{2}$$

Next we consider the relationship between lockdown orders and observed labor supply. We consider a singular model of employment without differentiating by industry. The advantage of such a formulation is the ready availability of weekly data. State governments track unemployment claims on a weekly basis, while more detailed information on particular industries is only available at the monthly level. Since responses to the COVID-19 pandemic were implemented quickly (and in some cases, withdrawn just as quickly), the use of weekly data is paramount to an accurate measure of employment effects.

Let $Ł^s_t$ represent the proportion of state's workforce employed in week t. We formulate another projection:

$$Ł^s_t = \phi_l(l_{s,t})' + \phi_t \mathbb{1}(t) + \phi_s \mathbb{1}(s) + \phi_R \mathbb{1}(s) + \epsilon_{s,t} \tag{3}$$

Where ϕ_l is the marginal reduction in employment owing to a specific, discrete lockdown order. ϕ_s represents state fixed effects to account for difference in policy, while ϕ_t is the time fixed effect in time t. $\phi_{s,t}$, $\phi_{l,t}$, and $\phi_{l,s}$ are the interaction effects. ξ^s_t represents the error term. We estimate these coefficients by finding:

Below we describe our procedure to estimate both equation (2) and (3) via panel regression. First we match each β_t with its state, recorded date, and lockdown phase. Lockdown phases were determined using data from The Washington Post In our estimation phase 1 corresponds to the most severe restrictions, phase 2 and 3 to gradually less restrictive orders, and phase 4 to little to no restrictions. As above, phases correspond to the initial reopening plan devised by the Washington State Department of Health.

Table 1: Panel Regression Results

	Base Model		Regional Controls	
Dependent Var	$\hat{\beta}$	$\hat{L}$	β	$\hat{L}$
Phase 1	-0.04	-5.374	-0.041	-5.179
	(0.01)	(0.588)	(0.009)	(0.571)
Phase 2	-0.033	-3.594	-0.031	-3.781
	(0.009)	(0.516)	(0.008)	(0.498)
Phase 3	-0.021	-2.061	-0.02	-2.013
	(0.01)	(0.568)	(0.009)	(0.547)
State FE	Yes	Yes	Yes	Yes
Regional FE	No	No	Yes	Yes

We reform our data set as a panel, with 16 weekly observations of β_t for each state. This data structure allows for estimation of (2). The coefficients of interest are naturally the lockdown coefficients and their state and time fixed effects.

To estimate equation (3) we need a measure of employment in each state. To this end, we utilize weekly unemployment claims to determine a measure of employment relative to February of 2020. Treating total employment in each state in February as "full employment", we compute the fraction of laborers employed on a weekly basis. We then match these time series to our panel data set, taking a weekly moving average of betas. Each observation corresponds to a state and week.

We estimate equations (2) and (3) using panel regression. The results of this exercise are presented below in table one below. We include results for two specifications: one with one time and state fixed effects, and one that introduces regional controls.

Next we consider the government's decision making process. The two projections estimated above are related through the state government's dynamic optimization problem. Each state government faces a weekly loss specification of the following form:

$$loss_g^s(L_t^s, d_t) = (1 - L_{t,s})^2 + e^{\omega} d_{t,c}^2$$

That is, in each period, the government's loss is a function of the level of unemployment and the number of realized pandemic deaths. Notice that loss is convex in both variables, although L_t is bounded above by one. Let T represent the government's planning horizon. In this problem, governments are myopic in that they consider losses only a finite number of periods into the future. To justify this assumption, consider that many state governments assumed that the pandemic would end by June or July of 2020. For instance, in mid-May of 2020, Governor De Santis of Florida declared that the state had succeeded in controlling the spread of COVID-19. Their initial lockdown decisions and subsequent reopening were made under this fundamentally myopic assumption. As such in our empirical section we will focus on a window of 16 weeks.

Across time the state government's problem can be expressed as,

$$\underset{l}{Min} \sum_{t=0}^{T} E[\eta^t((1 - L_{t,s})^2) + e^{\omega} d_{t,c}^2)] \tag{4}$$

Subject to constraints given by equation (2) and equation (3). Where η is the government's discount factor and l is the government's discrete lockdown decision. Since each component of this structural model will be estimated with weekly data, η will be incredibly close to 1. Notice that by taking the negative of the parenthetical expression, we can reformulate the above as a maximization problem. We accordingly formulate this problem as a dynamic program:

$$V(\beta_{t-2}) = \underset{l=\{l_0,l_1,l_2,l_3\}}{Max} \{L_t^2 - wd_t^2 + \eta V(\beta_{t-1})\} \tag{5}$$

Note that β_{t-2} will determine d_t, since time t deaths become infected in period $t-2$. In fact,the dependency of d_t on β can be recovered from the SIRD dynamics as

$$d_t = \delta\theta[\gamma(\frac{\beta_{t-2}S_{t-2}}{N} - \gamma - \theta + 2)I_{t-2} + (1-\theta)^2 R_{t-2}].$$

Thus in expectation the government knows how its decision will influence future deaths. The government's decision is further constrained by equations (1) and (2).

Now, in period t the state can indirectly pick β_t (and therefore the number of deaths in period t-2 and beyond) by choosing a lockdown order to impose. At the same time, the imposition of such an order would increase the unemployment rate, given by $1-L_t$. This dynamic problem admits a cutoff solution: once weekly infections rise to a high enough level, the cost of additional deaths exceeds the cost of economic damage, and the state imposes a lockdown order.

We need not explicitly consider the analytical solution to this problem. Indeed, accounting for the full consequences of the SIRD dynamics analytically would prove a difficult exercise. Instead, we simulate counterfactual realizations of d_t and L_t for each irreversible sequence in each state. We can then explicitly evaluate equation (4) to determine the time zero optimal lockdown order, given a value of ω.

In section 2.6 below we present our simulation methodology and our strategy for estimating each state's ω parameter.

2.4 Simulation and SMM Estimation

Using our estimates of equations (2) and (3), we now have the ability to simulate the interaction between the SIRD model and the government's sequence of decisions. These simulations will be matched to the observed sequences of lockdown orders through equation (4) by finding an optimal value of ω.

To conduct this estimation procedure, we first generate full sequences of potential lockdown orders. To reduce the size of this problem, we consider only what we call irreversible sequences. These are sequences in which lockdown orders cannot be reimposed. That is, once a state has opened up, it cannot revert to more severe lockdown orders. Limiting ourselves to such sequences greatly reduces the number of cases to consider[2].

For each irreversible sequence, we estimate the path of both β_t^s and L_t^s across our chosen time-window using estimates obtained from equations (3) and (4). The expected path of L_t^s stands on its own, but the path of β_t^s must be applied to the SIRD model described in section 2. The simulation of this model will allow us to derive the expected number of deaths each week from a given time series of counterfactual β_t^s.

In simulating the dynamics of COVID-19, we allow the model to operate on a daily basis, and then aggregate deaths by week. Results obtained from this process differ only slightly from simulating a weekly model, and then aggregating up. Additionally, we simulate pandemic spread based on individual state populations, using total recorded cases in the week prior to our simulation window to initialize the model. The data used to initialize the model are obtained from Youyang Gu, a data scientist who operates *covid19-projections.com*, a project dedicated to estimating the true number of infections across the United

[2]We generate these sequences using 10 million Markov-Chain Monte-Carlo simulations. We obtain 2991 sequences with 16 elements each.

States.

We thus now have a collection of weekly sequences for L_t^s and d_t^s corresponding to each state within our panel. Now, for a given value of ω we can calculate which sequence solves (5). We denote the sequence solving (5) for a particular value of $(\omega = \bar{\omega})$ as $\hat{l}(\bar{\omega})$.

Our problem now becomes one of selecting $\bar{\omega}$ to minimize the distance between observed lockdown sequences and predicted optimal sequences. Accordingly, the simulated method of moments condition for each state is given by:

$$\underset{\omega}{Min} \frac{1}{T} \sum_{t=1}^{T} [l_t^s - \hat{l}_t^s(\omega)]^2 \tag{6}$$

Where l_s is the observed lockdown sequence in state s and $\hat{l}_s(\bar{\omega})$ is the optimal sequence of lockdown orders derived from the above simulation when $\omega = \bar{\omega}$.

To quantify this expression, we assign each phase its numerical ranking, 1, 2, 3, or 4. Then the expression $(l_t^s - \hat{l}_t^s(\omega))^2$ provides a measure of distance between lockdown orders, that grows exponentially as orders become further apart. For instance, when a phase "1" is observed but a "4" is estimated, the corresponding penalty to the objective sum is 9; when elements of the estimated sequence match observations the corresponding penalty is 0.

The function $l_t^s(\omega)$ is discontinuous. Further, the objective (6), is riddled with local minima. Hence, conventional, gradient-based optimization routines will return incorrect, highly irregular estimates of ω. We thus apply a simulated annealing optimization method, as described in Belisle (1992). This technique essentially involves a stochastic grid search across function arguments. Given enough iterations, the algorithm will find global optima with probability one. Since, the mapping from ω to l is a map from a continuous, convex space to a discrete, non-convex space, the solution to (6) will be a continuous set of ω terms for each state. We use this algorithm to identify the minimum value of ω that solves equation (6).

Thus for many of the $\hat{\omega}$ estimates presented below, the true value may be higher. Indeed our estimates in table 2 are merely the smallest values of ω that would induce states to choose a lockdown sequence "close" to their observed choice.

The results of this optimization are reported for each 39 states in table 2 below. The column labeled “SSE” reports the value of the objective function, while the column labeled “sequence index” reports the position of the optimizing sequence in our matrix of irreversible sequences. Our second set of results are obtained through the panel model with regional controls, discussed further in section 3.4. This model yields estimates of $\hat{\omega}$ that broadly agree with the panel results, although the counterfactual results presented in the appendix are less stable to this formulation.

The values of $\hat{\omega}$ correspond somewhat neatly to lockdown severity. For instance, states like Arkansas and Oklahoma never imposed stay-at-home orders and moved quickly to lift restrictions on retail enterprises. They accordingly have values of ω below or rather close to zero. Similarly, states that waited one or two periods after the first confirmed deaths to impose restrictions, such as Delaware, have low values of $\hat{\omega}$. States that imposed severe restrictions like Washington tend to have relatively high values of $\hat{\omega}$. There is also a notable split by a state's political affiliation, with left-leaning states generally exhibiting higher values of $\hat{\omega}$.

Naturally, there are exceptions to this correlation. Kentucky and Mississippi, both conservative states, have remarkably high values of ω, while a handful of traditionally liberal states, such as Delaware and Colorado, have low values for their respective responsiveness parameter.

Given that states have unique initial conditions, the absolute interpretation of ω is challenging. States like New York and New Jersey had considerably higher rates of infection at the beginning of our panel. These states responded by imposing – and maintaining – stringent lockdown orders for most of the 16 week window. States like Connecticut also had a large number of initial infections. Connecticut locked down early, but began to lift restrictions after nine weeks. Our estimator internalizes this loosening of restrictions by assigning a lower value of ω to Connecticut.

The scale of our estimates of e^{ω} extend from 0.001 well into the hundreds. This variability, at first glance, may seem troubling. However, we are considering the square of both the d_t and $1 - L_t$ terms. As mentioned above, d_t represents the death rate per million residents, per week. In some states, this is likely to be quite low, and so an appropriate value of e^{ω} would have to be

Table 2: Estimates of $\hat{\omega}$

	Panel Model			Regional Controls		
State	$\hat{\omega}$	Index	SSE	$\hat{\omega}$	Index	SSE
Alabama	-3.61	32	7	-2.79	12	4
Arizona	2.08	1162	18	3.34	137	20
Arkansas	-2.73	3	9	-3.28	32	11
California	-1.96	764	3	-1.56	558	5
Colorado	-1.93	269	4	-2.19	700	5
Connecticut	-2.16	818	4	-3.08	632	5
Delaware	-3.77	32	14	-5.15	32	9
DC	2.32	1152	5	3.42	118	5
Florida	-3.69	9	5	-3.80	3	4
Georgia	-1.88	346	21	-2.19	268	24
Idaho	-4.61	32	7	-4.58	32	5
Illinois	0.28	1796	2	0.89	1152	4
Indiana	-4.14	32	13	-2.97	109	10
Iowa	-2.51	109	3	-2.03	40	7
Kansas	-1.44	209	5	-0.90	268	1
Kentucky	5.45	1162	14	4.57	533	38
Louisiana	-2.30	50	13	-0.93	1051	14
Maryland	0.11	469	4	-0.04	357	6
Massachusetts	0.26	1796	4	1.17	1162	6
Michigan	5.51	137	5	2.62	137	8
Minnesota	3.57	118	11	3.53	118	16
Mississippi	5.49	1152	18	4.35	98	27
Nevada	4.66	137	17	3.85	137	17
New Hampshire	5.07	137	5	3.43	137	8
New Jersey	5.03	137	12	3.61	137	12
New Mexico	2.31	118	19	3.57	137	21
New York	5.16	137	19	3.87	118	22
North Carolina	2.41	118	11	2.34	1162	16
Ohio	5.43	137	5	3.94	137	8
Oklahoma	-3.47	32	1	-3.97	32	5
Oregon	3.03	118	10	3.66	137	12
Pennsylvania	5.16	137	18	2.43	118	21
Rhode Island	-1.20	302	6	0.77	1152	9
South Carolina	5.27	137	26	4.53	137	26
Texas	-1.85	860	13	-2.14	863	14
Utah	-3.00	3	6	-2.81	9	7
Virginia	1.08	1152	2	1.40	1152	4
Washington	4.72	137	29	3.90	137	29
Wisconsin	5.23	137	8	3.72	137	11

Notes: This table lists recovered values of the responsiveness parameter $\hat{\omega}$, the index position of the implied optimal sequence $\hat{l}$, and the sum of squared errors given by $[l_t^s - \hat{l}_t^s(\omega)]^2$.

large in order to adequately capture a state's responsiveness.

Finally, we must consider the interpretation of $\hat{\omega}$. It would be incorrect to say that our estimates of e^{ω} represent the relative value of life in some linear fashion. That is, the government of Arizona does not care about its citizens' lives 700 times as much as, say, Indiana. Rather, the estimates of ω are more appropriately viewed as a relative ranking of responsiveness.

2.5 Counterfactual Generation

We next use our estimates of ω to model the results of state policies under counterfactual government preferences. This analysis better captures potential alternate outcomes than simply applying loose or stringent orders to each state, as it specifically accounts for the endogeneity of a lockdown policy. That is, State governments responded to the pandemic based on both their preferences and the prevailing initial conditions in their state. So, even a state with a relatively low value of ω (like Arkansas) may have optimally chosen a more stringent lockdown policy if their initial conditions resembled a state like New York. We thus refer to the below counterfactual outcomes as "policy consistent".

In table 3 below, we apply each state's estimated ω from the full panel model to every other state in our panel. We then compute the optimal policy response in each state. From these sequences we can then recover counter-factual death and unemployment rates consistent with the posited decision making process.

This exercise allows us to formulate a realistic measure of the fundamental policy trade-offs faced during the first 16 weeks of the COVID-19 pandemic. Table 3 below presents the national counter-factual outcomes derived from each state's estimated $\hat{\omega}$. The Column labeled "Excess Deaths" presents the predicted deviation in absolute terms from observed deaths between March 20th and July 10th, a period of 16 weeks that corresponds to our estimation window. The column labelled "Excess Urate" presents the deviation of the mean national unemployment rate over that same time period.

This table allows us to draw several conclusions about a hypothetical national lockdown policy. If a national lockdown were conducted with a relatively low value of ω, analogous to, say, the state of Idaho, then deaths would have increased by roughly 84,000, but the national unemployment rate would have been 2.51% lower. On the other hand, a heavy national lockdown policy, comparable to that of, say, Washington state, would have only decreased deaths modestly, but increased unemployment by nearly 1%.

The United State labor force consists of roughly 160 million workers. Continuing with our Washington/Idaho comparison, a relatively lax policy response implemented on a national level would have prevented the loss of an additional 3.2 million jobs. Simply put, the economy could have purchased 50 jobs for the cost of one human life (3.2 million jobs/84,000 lives). If we consider the opposite counterfactual scenario – a national lockdown with a responsiveness similar to Washington state – we find a trade off ratio of approximately 792 jobs to one human life.

The final column in this table presents the above calculation for each state within our panel. Notice that states like Idaho and Florida, which made a show of reopening quickly, have fittingly low implied life valuations, while states that adopted more cautious approaches tend to have higher implied life valuations. As with the recovery of the $\hat{\omega}$, the values in this final column reflect a partisan divide. States with relatively lows values tend to be known as right-leaning, while states with relatively high values appear to be more liberal. There are, naturally, exceptions to this correlation – New Jersey and Mississippi for instance have responsiveness parameters well outside what their politics might suggest.

3 Household Response and Welfare Analysis

In the following section we specify a model of household behavior in response to the decision process posited above. The model is parsimonious, flexible, and lends itself well to simulation. As such, we will combine this model with the decision rules and associated paths for infection and employment obtained in section 1. Together, these two models will allow us to assess the welfare implications of COVID-19 policy responses.

We will consider two separate exercises. In the first application we use the decision rules adopted by each state to compute a measure of expected utility for households within that state – essentially an assessment of each state's policy efficacy. The second exercise envisions a hypothetical national policy

Table 3: Recovery of Implied Life Valuations

State	Log($\hat{\omega}$)	$\hat{D}$	100-$\hat{L}$	Excess Deaths	Excess Urate	Lives/Jobs
Alabama	-3.61	180,675	10.333	45,221	-1.967	69.58
Arizona	2.07	133,227	13.114	-2,227	0.814	584.53
Arkansas	-2.73	159,728	10.830	24,274	-1.470	96.92
California	-1.96	148,030	11.288	12,576	-1.012	128.70
Colorado	-1.93	147,453	11.321	11,999	-0.979	130.57
Connecticut	-2.16	150,490	11.162	15,036	-1.138	121.07
Delaware	-3.77	186,204	10.233	50,750	-2.067	65.15
DC	2.32	133186	13.151	-2268	0.851	600.65
Florida	-3.69	183,142	10.288	47,688	-2.012	67.51
Georgia	-1.88	147,055	11.339	11,601	-0.961	132.56
Idaho	-4.61	219,900	9.791	84,446	-2.509	47.54
Illinois	0.28	134,990	12.436	-464	0.136	471.09
Indiana	-4.14	198,635	10.041	63,181	-2.259	57.20
Iowa	-2.51	155,648	10.959	20,194	-1.341	106.28
Kansas	-1.44	142,879	11.573	7,425	-0.727	156.61
Kentucky	5.45	132,932	13.616	-2,522	1.316	834.86
Louisiana	-2.30	152,393	11.089	16,939	-1.211	114.36
Maryland	0.11	135,324	12.379	-130	0.079	968.03
Massachusetts	0.26	135,023	12.431	-431	0.131	486.24
Michigan	5.51	132,931	13.617	-2,523	1.317	835.26
Minnesota	3.57	132,991	13.418	-2,463	1.118	726.03
Mississippi	5.49	132,932	13.616	-2,522	1.316	834.67
Nevada	4.66	132,946	13.535	-2,508	1.235	788.21
New Hampshire	5.07	132,940	13.562	-2,514	1.262	803.18
New Jersey	5.03	132,941	13.557	-2,513	1.257	800.42
New Mexico	2.31	133,187	13.151	-2,267	0.851	600.41
New York	5.16	132,939	13.568	-2,515	1.268	806.90
North Carolina	2.41	133,154	13.187	-2,300	0.887	617.02
Ohio	5.43	132,932	13.612	-2,522	1.312	832.22
Oklahoma	-3.47	176,290	10.418	40,836	-1.882	73.74
Oregon	3.03	133,043	13.309	-2,411	1.009	669.26
Pennsylvania	5.16	132,936	13.590	-2,518	1.290	819.46
Rhode Island	-1.20	141,096	11.701	5,642	-0.599	170.00
South Carolina	5.27	132,935	13.600	-2,519	1.300	825.52
Texas	-1.85	146,492	11.364	11,038	-0.936	135.62
Utah	-3.00	164,853	10.683	29,399	-1.617	88.02
Virginia	1.08	133,871	12.767	-1,583	0.467	471.61
Washington	4.72	132,945	13.543	-2,509	1.243	792.43
Wisconsin	5.23	132,935	13.596	-2,519	1.296	823.09

Notes: For each of the recovered values of $\hat{\omega}$, we compute the optimal response sequence for each state. We then use the SIRD model above to simulate national employment and death outcomes across the first 16 weeks of the COVID-19 pandemic. The table above presents these numbers, along with comparisons to observed deaths and observed employment figures. By converting the employment percentages to counts, we can formulate the implied value of each life in terms of employment counts in each state, presented in the final column.

response using each state's estimated ω parameter. We apply the ω parameter of each state to the initial conditions of every state, compute hypothetical paths for viral spread and employment, then use our household model to assess the welfare rankings of each ω value. Below, we introduce the model.

3.1 A Stylized Model of Household Response

The household's objective is to maximize utility over the course of the pandemic by choosing consumption and asset holdings in each period, taking the government's policy sequence as given. Formally, households solve:

$$Max_{t=0}^{T} \sum \eta^t E_0[U(c_t) + \bar{U} + \hat{U_{s,t}}] \text{ s.t}$$

$$a_{t+1} \leq w_t + u_t + p_t + (1+r)a_t - c_t$$

$$a \geq \hat{a}$$

Where c_t is period consumption, U is an increasing, concave utility function, $\bar{U}$ is the baseline utility of being alive, and $\hat{U_{s,t}}$ is the utility of occupying health state s in time t. We let η denote the household's discount factor. w_t is the wage earned by an employed household, while u_t is the unemployment benefit received by an unemployed household, and p_t is any pension income that a household receives. Let y_t denote income in period t, derived from wages, unemployment benefits, or a pension.

The household can save by purchasing one-period risk-free bonds that return $(1+r)$ per dollar invested. a_t is the level of assets (bonds) held by a household in time t. Household savings is defined as the period change in asset holdings, given by $s_t = a_{t+1} - a_t$.

The timing of the household's decision is as follows:

1. The period begins and the household realizes its time t state
2. The household realizes its income y_t based on its current state
3. The household allocates period consumption from asset holdings and period income
4. The period ends

Notice that consumption is constrained from above by the value $y_t + a_t$. Hence, the household's first order optimality condition is given by,

$$u'(c_t) = max\{\eta(1+r)E_t[u'(c_{t+1})], u'(y_t + a_t)\} \tag{7}$$

Let $\sigma(a_t, z_t) = c_t$ denote the policy function derived from the above problem.

There are two classes of household, old and young. Young households can assume four distinct states corresponding to employment, unemployment, sickness, and death. In each period, the probability of employment and infection states are recovered from the structural equations and SIRD dynamics presented above. We assume that infected individuals are not working, and that death is an absorbing state – once a household enters a death state it cannot be revived. Employed households receive a wage w_t in each period, while both unemployed and sick households receive an unemployment benefit, u_t. Dead households receive no income.

Old households face a nearly identical optimization problem, except they have no employment state. Rather, old households face only three states, healthy, sick, and dead. In the first two states an old household collects a pension (rather than a wage) and decides on an optimal level of assets. Death is again an absorbing state for old households.

Throughout the following analysis, we set $w_t = 1.0$, $u_t = 0.25$, and $p_t = 0.33$. The household's discount factor η is set to 0.9999, while the return on bonds is set to a modest $r = 0.0004$ (a roughly 2% annualized return). We further set $\bar{U} = 0$, so that there is no additive adjustment to the utility of susceptible and recovered households. Finally, we set $U_{I,t} = .50$ and $U_{d,t} = 5$, so that sick and dead households suffer a penalty to period utility so long as they remain in that state. The value of $U_{d,t}$ is obtained from Martin and Pyndyk (2019), and is taken to correspond to the Statistical Value of Life literature.

Let the subscripts E, U, I and D represent the employment state, the unemployment state, the infected state, and the death state respectively. Then, in every period young households face transition probabilities given by,

$$\mathrm{M}_t^y = \begin{bmatrix} P_{EE}^t & P_{EU}^t & P_{EI}^t & 0 \\ P_{UE}^t & P_{UU}^t & P_{UI}^t & 0 \\ 0 & P_{IU}^t & P_{II}^t & P_D^t \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

Where P_{EE}^t is the probability that a household employed in period t remains employed in period $t+1$. Let L_t denote the employment rate implied by the policy sequence induced by ω. Let N be the size of the population and I_t be the number of infected persons in time t.

The per-period transition probabilities are empirically recovered from both equation (3) and the SIRD dynamics implied by each state's ω parameter. We recover the probability of retaining an employment state in time t as, $P_{EE}^t = \hat{L}_t + \frac{1}{2}(1 - \hat{L}_t)$. The infection probabilities in both the employed and unemployed state are assumed to be equal and are given by, $P_{EI}^t = P_{UI}^t = \frac{I_t}{N}$. We then compute $P_{EU}^t = 1 - P_{EE}^t - P_{EI}^t$. In the unemployment state, $P_{UE}^t = L_t - \frac{1}{2}(1 - L_t)$ $P_{UU}^t = 1 - P_{UE}^t - P_{UI}^t$. Finally, in the infected state the probabilities of recovery, infection, and death are given by, $P_{IU}^t = .70$, $P_{II}^t = .29$, and $P_{ID}^t = .001$.

Let H denote the healthy state for an old household, let I denote the infection state and D denote the death state. The transition probabilities for old households are given by,

$$\mathrm{M}_t^o = \begin{bmatrix} P_{HH}^t & P_{HI}^t & 0 \\ P_{IH}^t & P_{II}^t & P_{ID}^t \\ 0 & 0 & 1 \end{bmatrix}$$

Where we now set $P_{HI}^t = \frac{I_t}{N}$ and $P_{HH}^t = 1 - \frac{I_t}{N}$. Again using fatality rates from the *Our World in Data* website, we set $P_{ID}^t = .025$, a value that corresponds to the case fatality rate of individuals 65 and older. Similarly,the average duration of a COVID-19 infection is longer for elderly households. We thus set $P_{IH}^t = 0.225$ and $P_{II}^t = 0.775$.

3.2 Exercise One: Evaluation of State Policies

In our first application of this model, we calculate the response of households to the policy sequences adopted by each state. We use projection equations (2) and (3) to obtain both the expected proportion of unemployed workers $(1-\hat{L}_t)$

and the expected values of the SIRD β parameter in every week between March 20th and and July 10th 2020. We then simulate the SIRD dynamics implied by the sequence of β terms and initial values for I_t. As above, the value $\frac{I_t}{S_t}$ will yield infection probabilities in each period and state.

Following July 10th, we allow the infection and unemployment probabilities to converge to zero over 12 periods, mirroring the trough reached in infections and deaths in late October of 2020. The model and simulations make no attempt to examine the second wave of the COVID-19 pandemic, which lasted between November 2020 and March of 2021. Incorporating such additional data into this framework would require an accounting of vaccine policy that is outside the scope of our present analysis.

Naturally, different households will experience different trajectories through this time period. Some households will be spared unemployment, sickness, or death while others might take less fortunate paths through the pandemic. Since our transition probabilities evolve weekly, we cannot simply compute an invariant distribution of some fixed Markov process. Instead we utilize Monte-Carlo simulations to determine a distribution of household states in each period.

Let z_t denote the state occupied by a household at time t, and y_t denote the household's corresponding income level. We approximate $\hat{\sigma}(a_t, z_t)$ by first constructing a 500x4 grid of asset, state combinations, setting $\bar{a} = 0$ and $a_{max} = 10$. We similarly set arbitrary grid points to initialize our approximation of $\hat{\sigma}$. For each pair of asset values and health states we find the value of c_t^* that corresponds to our model's policy function. That is, we numerically solve,

$$Min(u'(c_t) - Max\{\eta(1+r)E_z[u'(\hat{\sigma}(R(1+r)(a_t - c_t) + y_t, z_t))], u'(a_t)\})^2 \quad (8)$$

We then set $\hat{\sigma}(a_t, z_t) = c_t^*$. We conduct this optimisation procedure for every value of a_t and z_t to obtain a grid of values for $\hat{\sigma}()$. We repeat the procedure until the points of our $\hat{\sigma}$ grid converge. Formally, we iterate until

$$Max|\hat{\sigma}_{i+1} - \hat{\sigma}_i| < .001 \quad (9)$$

Where i denotes the current iteration. We then quadratic interpolation to approximate the form of the policy function. The resulting function will allow the calculation of optimal consumption decision for every (a_t, z_t) pair. Since the transition probabilities change every period, the expected value component of equation (8) will evolve depending on the current time and state. We thus conduct the above procedure for every state and every week in our simulation. The result is a set of decision rules for every state, time, health state, and level of assets.

Using these results, and the transition matrices we've calculated for each state, we simulate 100,000 household trajectories in each geographic state. Clearly, an individual household's path of consumption and savings through the pandemic will depend not just on its realization of health and employment states, but also its initial level of assets. We accordingly assign young households initial assets according to the following proportions: 50% of households have only one income unit in asset holdings; assets holdings equal to 1.5, 2, 3 and 4 are all held by 10% of the population; 5% of the population has asset holdings equal to 5 and 10 units. For old households the distribution of initial assets assigns 50% of households 3 units, 20% of households 4 units, and the final 30% of households 5 units.

Averaging the results of these simulations, allows us to compute expected utility for each household type in each geographic state, along with aggregated paths for household consumption and savings. The results of these utility calculations are given in the table below. Note that expected utility is calculated as the weighted average of $E(U_y)$ and $E(U_o)$, with weights corresponding to each state's proportion of elderly citizens.

We then transform these measures of utility into consumption units and conduct comparisons to two baseline measures: consumption equivalent utility in a risk-free model and in a model with no policy interventions. For the first comparison, we simply find the realized level of expected consumption in a model where the probabilities for unemployment, sickness and death are zero. For our second comparison, we use our estimates of equations (3) and (4), and the SIRD dynamics to determine the implied risk of infection and unemployment when polices are set to 0 in all periods.

Converting the recovered utility values into consumption equivalent units requires some manipulation. Let c^* and $\bar{U}^*$ denote the levels of consumption and utility penalty realized in a baseline scenario. To determine the welfare implications of each state's policy response, we calculate the proportional change in consumption that a typical household would need to be indifferent between a particular response and a baseline scenario. Formally, we calculate a value of λ that solves,

$$\sum_t \sum_z \beta^t P_z \left(\frac{((1+\lambda)c_{t,z})^{1-\gamma}}{1-\gamma} - \bar{U}_{t,z} \right) = \sum_t \sum_z \beta^t P^*_z \left(\frac{((1+\lambda)c^*_{t,z})^{1-\gamma}}{1-\gamma} - \bar{U}^*_{t,z} \right) \tag{10}$$

Let X^* denote the value of the right-hand side of this equation. With some manipulation, we can recover λ as,

$$\lambda = \left[\frac{X^* - \sum_t \sum_z \beta^t P_z \bar{U}^{t,z}}{\sum_t \sum_z \beta^t \frac{c_{t,z}^{1-\gamma}}{1-\gamma}} \right]^{\frac{1}{1-\gamma}} - 1 \tag{11}$$

The results of this exercise are presented in table 3 below. The CEU columns present the change in consumption relative to each baseline needed to render an average household indifferent between reality and the baseline. For instance a typical household in Washington State would be indifferent between living through 30 weeks of COVID-19 and a 11.05 % reduction in consumption but no risk. Similarly, a typical Washington household would need an extra 8.43% consumption in each period to compensate them for a (hypothetical) absence of any policy response.

Notice that states with modest lockdown policies and a high proportion of elderly citizens, tend to have the lowest (most negative) change in consumption equivalent units relative to the risk-free baseline. Indeed, states with the most lax restrictions, such as Idaho and Indiana, have low values of expected utility even for young households, although it is important to note that the values for $E(U_y)$ do vary considerably across states.

The results of our second comparison allow us to formulate a number of conclusions. First, the final column of table 4 indicates that most states were correct to adopt some policy response. Even states that adopted minimal restrictions realized an improvement over the "no mitigation" scenario. Second, states who realized a lower level of utility than the "no mitigation" scenario were states that hesitated in their response to the pandemic. New York, New Jersey, and Louisiana specifically allowed the virus to spread for two weeks without a significant policy response. When these states did respond, the re-

Table 4: Welfare Effects of Observed Policy Responses

			Risk Free Model	No Mitigation
State	$\hat{\omega}$	Weight	CEU	CEU
Mississippi	5.49	0.159	-15.00%	-12.09%
New Jersey	5.03	0.161	-27.97%	-9.79%
Louisiana	-2.30	0.154	-24.20%	-5.89%
New York	5.16	0.164	-28.83%	-3.33%
Kentucky	5.45	0.164	-6.67%	-1.79%
Florida	-3.69	0.205	-13.16%	1.03%
Connecticut	-2.16	0.172	-18.64%	1.29%
DC	2.32	0.121	-11.11%	3.70%
Maryland	0.11	0.154	-8.35%	4.05%
Minnesota	3.57	0.159	-8.50%	5.47%
Utah	-3.00	0.111	-9.65%	6.36%
Idaho	-4.61	0.159	-14.02%	6.57%
Texas	-1.85	0.126	-8.84%	7.19%
Oklahoma	-3.47	0.157	-11.91%	7.60%
Oregon	3.03	0.176	-8.71%	7.65%
Iowa	-2.51	0.171	-9.75%	7.83%
Arkansas	-2.73	0.17	-8.98%	7.90%
Alabama	-3.61	0.169	-11.62%	8.16%
Kansas	-1.44	0.159	-9.14%	8.33%
Arizona	2.08	0.175	-9.32%	8.34%
New Hampshire	5.07	0.181	-10.63%	8.43%
Washington	4.72	0.154	-11.05%	8.60%
Nevada	4.66	0.157	-11.12%	8.84%
Ohio	5.43	0.171	-10.17%	9.16%
Virginia	1.08	0.154	-9.72%	9.36%
North Carolina	2.41	0.163	-9.04%	9.39%
Wisconsin	5.23	0.17	-10.37%	9.57%
South Carolina	5.27	0.177	-10.39%	9.64%
Rhode Island	-1.20	0.172	-14.42%	9.94%
New Mexico	2.31	0.175	-9.15%	9.96%
Illinois	0.28	0.156	-11.36%	10.10%
Indiana	-4.14	0.158	-13.92%	10.47%
Massachusetts	0.26	0.165	-17.16%	10.52%
Pennsylvania	5.16	0.182	-15.22%	11.04%
Delaware	-3.77	0.187	-13.53%	11.23%
Michigan	5.51	0.172	-17.75%	11.37%
Colorado	-1.93	0.142	-12.09%	12.10%
Georgia	-1.88	0.139	-12.35%	12.18%
California	-1.96	0.143	-13.82%	13.67%

Notes: The above table presents the welfare effects of each state's adopted policy response in consumption equivalent units. Measures here apply to the 31 weeks between March of 2020 and October of 2020. The Risk Free comparison column shows what reduction in consumption would render a typical household indifferent between 31 weeks of pandemic and a world with no risk. Similarly, the No Mitigation column shows the improvement – in consumption equivalent units – engendered by the state's policy response.

sult was profoundly depressed employment *and* high levels of viral spread – the worst of both worlds, so to speak.

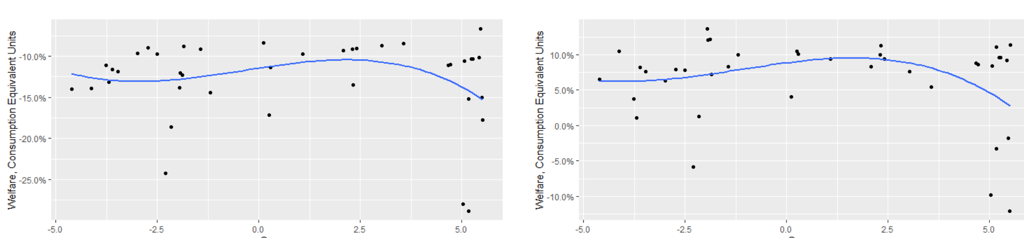
Mississippi and Kentucky both responded with several weeks of stay-at-home orders, followed by nearly two months of additional restrictions, despite modest levels of initial infections. Hence, the model assigns them a lower level of utility than would be realized in a baseline model with no risk.

The relationship between $\hat{\omega}$ and expected household utility is not entirely clear in evaluating individual state policies. In figure 1 below, we plot $\hat{\omega}$ against the welfare effects obtained through this exercise. There appears to be a general upward sloping relationship, although it is marred by the presence of two outlier observations corresponding to New York and New Jersey.

Indeed, the relationship between ω and welfare outcomes is distorted by differences in initial conditions across states. For example, the state of Kansas, which has a low value for ω, began the pandemic with a relatively low level of infections. Even with a modest sequence of responses, the utility realized in Kansas relative to the risk free model is still quite high. However, a state like New York, which has a high value for ω, experienced a staggering number of infections in the opening weeks of the Pandemic. As such, its utility realization relative to the risk free model will be substantially more negative.

The distortion introduced by differences in initial conditions prevents us from adequately evaluating the welfare implications of responsiveness levels. To account for these effects, we assign each state the same initial conditions: those that prevailed across the entire United States in February of 2020.

Figure 1: $\hat{\omega}$ and Welfare Gains and Lossess



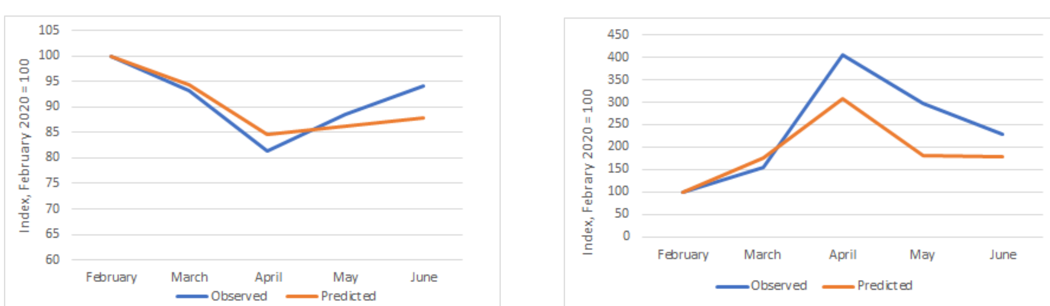
The diagram on the left present the change in consumption equivalent utility relative to a risk-free baseline for each state, plotted against the ω values of each state. The figure on the right presents the same measure, but relative to a no mitigation baseline. Notice that there is no clear relationship between ω and the utility gains and losses.

Before we conduct our national counterfactual exercise, we present key business cycle moments and our models corresponding predictions over the first 5 months of the pandemic. We aggregate consumption and savings predictions by first calculating average household consumption and savings for every week, in each state in the panel. We then apply each state's population weight to their predicted values of consumption and savings across the four and one half weeks in each month. We normalize aggregated consumption and savings to equal 100 in February of 2020; we compare our obtained values to the Consumption Expenditures and Households Savings Rate series obtained from FRED. The results of this comparison are presented below.

While the model matches data qualitatively – a sharp contraction in consumption followed by a gradually strengthening recovery – the moments do not match perfectly. Indeed, the model presented above predicts a fairly accurate drop in consumption, but a more gradual recovery than is observed in data. However, the percentage deviation between prediction and reality is not large, which suggests our model is an adequate description of reality. The mean squared prediction error from consumption is 2.6%. The model's deviation from the observed path of households savings is larger, but the time series still matches the qualitative behavior of savings. Both time series are presented in figure 2 below, alongside their empirical analogs.

In the appendix, we present time-series plots of savings and consumption for both young and old households, in each state.

Figure 2: Aggregated Consumption and Savings



3.3 Exercise Two: Evaluation of National Policies

During the initial months of the COVID-19 pandemic, state governments found themselves wholly responsible for the formulation and implementation of policy responses. In this section, we envision a series of comprehensive national policy responses derived from each state's ω parameter. That is, we use each ω to calculate a corresponding sequence of policy responses across all states. The resulting paths of β and L allow us to compare hypothetical national polices using the household response model presented above.

This exercise allows us to assess the effect of governmental responsiveness, as captured by the ω parameter, in a context not distorted by heterogeneous initial conditions. In exercise one above, the welfare effects of each states' response, depended on its sequence of policy orders *and* its initial conditions. This is why states like New York and New Jersey had such low values of consumption equivalent utility compared to a risk-free baseline. In formulating this exercise, we remove the effect of initial conditions by applying each states $\hat{\omega}$ to every state in our panel.

The procedure to recover household response paths and expected utility are exactly the same as above – only the sequences of transition matrices are different. We construct the sequence of transition matrices for each responsiveness level by selecting a sequence that solves the objective in equation (4) in each state. We then take the counterfactual paths of infections and employment to recover a sequence of probabilities for employed, unemployed, and infected states. We weight these probabilities by each state's population to derive a final, national sequence of transition probabilities that we place into a sequence of matrices.

We present the results of this exercise in table 5 below. Note that for the calculation of $E(U)$ and subsequent derivations of equivalent consumption units we use 0.165 as the proportion of elderly citizens. As with exercise one, we compare our recovered consumption equivalent utility to two baseline outcomes, one in which there is no policy responses and one in which the pandemic does not occur.

The results of this section suggest that exceedingly lax restrictions would not be optimal for a coordinated national response. The increased risk of infection and death are sufficient to create lower levels of expected utility in states like Idaho and Florida. That is, the increase in expected utility resulting from higher employment probabilities does not outweigh the increased risk of entering an infection or death state. This result holds in comparisons to both posited baseline models.

The magnitude of these changes (relative to both baseline scenarios) are modest compared to exercise one. This is expected, as national outcomes would tend to smooth-out excessive declines in utility owing to stark initial conditions. For instance, the effects of New York and New Jersey would be averaged out by states like Washington and Oregon, which had comparatively few cases at the pandemic's onset. The welfare effects presented in the table below are therefore much less volatile than the figures given in table 4 above.

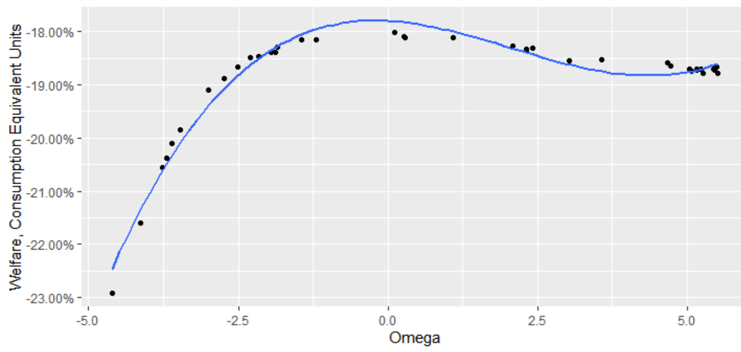
Table 5: Welfare Effects of National Counterfactuals

			Risk Free	**No Mitigation**
State	Log(w)	Weight	CEU	CEU
Alabama	-3.612	0.169	-20.11%	3.85%
Arizona	2.076	0.175	-18.27%	5.47%
Arkansas	-2.733	0.17	-18.87%	4.90%
California	-1.959	0.143	-18.38%	5.32%
Colorado	-1.931	0.142	-18.37%	5.34%
Connecticut	-2.163	0.172	-18.47%	5.25%
Delaware	-3.772	0.187	-20.56%	3.48%
District of Columbia	2.317	0.121	-18.34%	5.41%
Florida	-3.689	0.205	-20.38%	3.63%
Georgia	-1.884	0.139	-18.39%	5.32%
Idaho	-4.605	0.159	-22.92%	1.50%
Illinois	0.280	0.156	-18.11%	5.59%
Indiana	-4.135	0.158	-21.59%	2.62%
Iowa	-2.513	0.171	-18.66%	5.07%
Kansas	-1.444	0.159	-18.16%	5.52%
Kentucky	5.455	0.164	-18.73%	5.11%
Louisiana	-2.303	0.154	-18.49%	5.23%
Maryland	0.112	0.154	-18.02%	5.66%
Massachusetts	0.259	0.165	-18.10%	5.60%
Michigan	5.510	0.172	-18.78%	5.07%
Minnesota	3.570	0.159	-18.53%	5.27%
Mississippi	5.489	0.159	-18.67%	5.16%
Nevada	4.659	0.157	-18.59%	5.22%
New Hampshire	5.068	0.181	-18.75%	5.09%
New Jersey	5.029	0.161	-18.71%	5.12%
New Mexico	2.307	0.175	-18.33%	5.42%
New York	5.162	0.164	-18.70%	5.13%
North Carolina	2.411	0.163	-18.31%	5.44%
Ohio	5.434	0.171	-18.70%	5.14%
Oklahoma	-3.474	0.157	-19.84%	4.08%
Oregon	3.029	0.176	-18.54%	5.25%
Pennsylvania	5.163	0.182	-18.72%	5.11%
Rhode Island	-1.201	0.172	-18.16%	5.53%
South Carolina	5.267	0.177	-18.79%	5.06%
Texas	-1.852	0.126	-18.29%	5.41%
Utah	-2.996	0.111	-19.10%	4.70%
Virginia	1.079	0.154	-18.11%	5.60%
Washington	4.716	0.154	-18.64%	5.18%
Wisconsin	5.229	0.17	-18.71%	5.13%

Notes: In the table above, we present the welfare implications of national policy responses over the 31 week time horizon from March to October of 2020.We use each state's $\hat{\omega}$ to compute a sequence of policy orders in each state and then aggregate. The welfare effect, in consumption equivalent units, relative to a No Risk outcome and a No Mitigation are given in the final two columns of the table.

In figure 3 above, we plot each state's $\hat{\omega}$ value against its consumption equivalent utility, relative to a baseline risk free scenario. The plot suggests

Figure 3: National Policy Analysis



that low values of $\hat{\omega}$ lead to suboptimal policy responses that, in turn, create a heightened risk of infection and death. Further, the plot suggests that increases in $\hat{\omega}$ beyond a certain point actually reduce welfare. In other words, moderate policy responses are, at a national level, preferable to stringent orders in terms of expected household utility across the first wave of the COVID-19 pandemic.

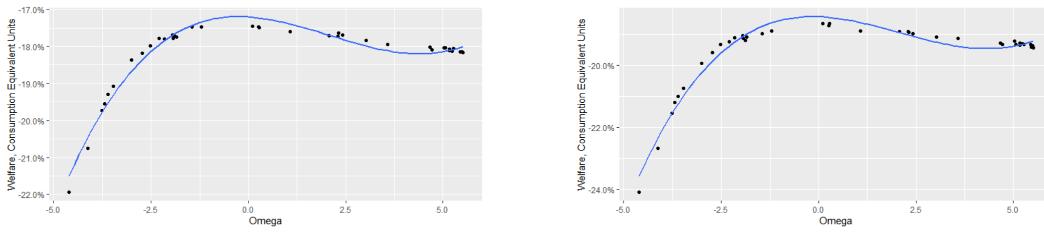
3.4 Robustness Checks

The central result of the above analysis is that moderate national policies outperform both overly stringent and overly lax responses. In this section we consider a number of modifications to the model and demonstrate that this result is stable. First we consider alternate values for the parameter $\bar{U}_d$. Martin and Pyndyk (2019) posit a range of values between 3 and 10 times period income for this parameter. We consider the values $\bar{U}_d = 3$ and $\bar{U}_d = 7$.

We repeat the national simulation exercises above using these penalties. Tables 5 and 6 in the appendix present consumption equivalent utility relative to both baselines under these alternate parameterizations. We consider both the national counterfactual exercise and the evaluation of in-state policies. The central result of the national counterfactual exercise is unchanged: moderate policies promote higher levels of consumption equivalent utility. The two figures below demonstrate this result. Indeed the ordering given in table 4 is not particularly sensitive to alternate values of $\bar{U}$. Both higher and lower penalty values yield a similar ordering.

Our second robustness check adds regional controls to the panel regression presented in section 2. These controls allow us to account for variation in infection rates and joblessness that stem from interstate spillovers. For example, state proximate to New York. The addition of these controls does not alter the fundamental conclusions of our analysis, although the ordering of consumption

Figure 4: Consumption Equivalent Utility, $\bar{U} = 3$ and $\bar{U} = 7$

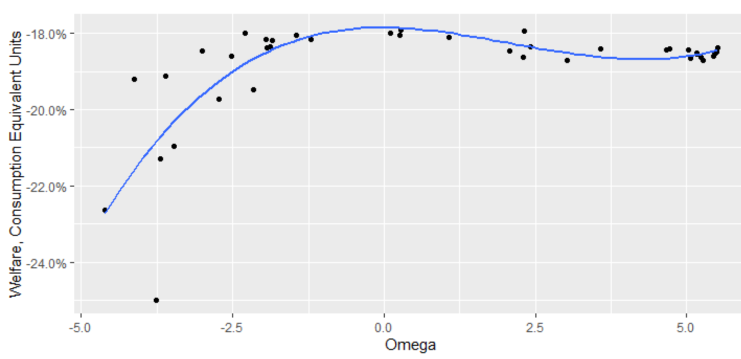


equivalent utility outcomes does change.

The results of the national counterfactual exercise are summarized in figure below, while precise figures for consumption equivalent utility can be found in tables 7 and 8 in the appendix.

Next, we re-estimate equations (2) and (3) using regional controls to account for spillover effects between states. We then repeat the recovery of $\hat{\omega}$ and the simulation exercise described above. Once again, the central result that moderate policies operate most effectively on a national scale is unchanged, as demonstrated in figure below.

Figure 5: National Policy Analysis – Regional Controls



The full set of results for this robustness check are presented in table in the appendix.

4 Conclusion

Not all states place an equal priority on pandemic deaths relative to employment outcomes. As demonstrated in section 2, state with lower relative valuations of life tend to adopt more relaxed policy response endogenously. States with a relatively high responsiveness value of follow more strict lockdown paths. Thus, each state's valuation of life relative to employment, as captured by the parameter ω, determined the severity of labor market conditions at the outset of the COVID-19 pandemic. However, states that adopted such polices also experienced more modest levels of viral spread – leading to fewer infections and deaths.

The responsiveness parameter ω can be used to formulate counterfactual national outcomes for both employment and deaths. These estimates can then be applied to recover a minimum implied valuation of life in each state. These values represent present a single figure that captures the number of jobs equivalent to a single human life in each state. We find a general correlation between a state's implied life valuation and its politics – conservative states tend to have low life valuations, while liberal states generally exhibit a valuation.

Finally, we use the SIRD dynamics and our counterfactual environment to evaluate state policies and their hypothetical national analogs using a stylized model of household behavior. This model demonstrates that an overly relaxed policy response to the pandemic is generally not optimal – especially in states with a large proportion of elderly citizens. Nationally, low values of ω would lead to suboptimal outcomes – the increased risk of infection and death outweigh the benefits of a lower unemployment rate. However, after a certain point higher values of ω, and the additional restrictions implied by them, no longer afford household's additional gains in net utility through lower infection and death probabilities.

This central result is robust to both alternative values of the death-state penalty, $\bar{U}$, and to the addition of regional controls in structural equations (2) and (3).

5 Appendix

There are three sections in the appendix. Section one presents the full set of results for the robustness checks outlined in section 3.4 above. Section two presents the dynamic plots of β_t across the first sixteen weeks of the pandemic. Finally, section three presents the household impulse responses of consumption and savings for each state in our panel.

5.1 Robustness Checks

Table 6: Welfare Effects, National Counterfactuals with alternate Parameterization

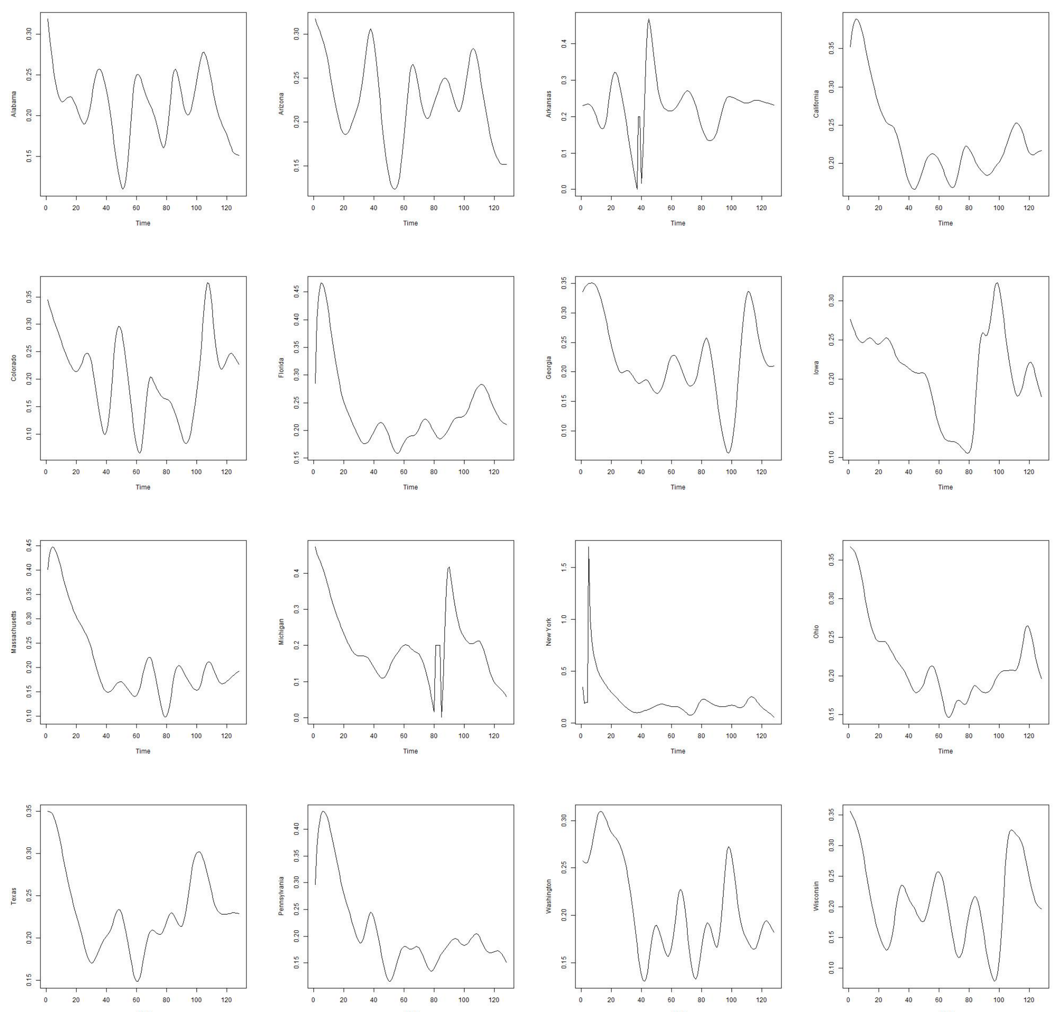
		$\bar{U} = 3$		$\bar{U} = 7$	
State	Log(w)	No Risk	No Mitigation	No Risk	No Mitigation
Alabama	-3.61	-19.30%	4.58%	-20.99%	3.06%
Arizona	2.08	-17.71%	5.97%	-18.91%	4.90%
Arkansas	-2.73	-18.19%	5.51%	-19.57%	4.27%
California	-1.96	-17.70%	5.94%	-19.04%	4.74%
Colorado	-1.93	-17.78%	5.87%	-19.13%	4.66%
Connecticut	-2.16	-17.81%	5.84%	-19.09%	4.69%
Delaware	-3.77	-19.73%	4.22%	-21.55%	2.59%
District of Columbia	2.32	-17.64%	6.04%	-18.92%	4.90%
Florida	-3.69	-19.55%	4.37%	-21.19%	2.90%
Georgia	-1.88	-17.72%	5.92%	-19.18%	4.62%
Idaho	-4.61	-21.94%	2.38%	-24.10%	0.45%
Illinois	0.28	-17.48%	6.15%	-18.64%	5.11%
Indiana	-4.14	-20.75%	3.37%	-22.67%	1.66%
Iowa	-2.51	-17.99%	5.68%	-19.31%	4.49%
Kansas	-1.44	-17.46%	6.14%	-18.96%	4.81%
Kentucky	5.45	-18.15%	5.63%	-19.40%	4.51%
Louisiana	-2.30	-17.78%	5.86%	-19.22%	4.57%
Maryland	0.11	-17.46%	6.17%	-18.63%	5.11%
Massachusetts	0.26	-17.47%	6.16%	-18.72%	5.05%
Michigan	5.51	-18.16%	5.62%	-19.42%	4.49%
Minnesota	3.57	-17.94%	5.79%	-19.11%	4.75%
Mississippi	5.49	-18.15%	5.63%	-19.36%	4.55%
Nevada	4.66	-18.02%	5.73%	-19.28%	4.61%
New Hampshire	5.07	-18.04%	5.72%	-19.33%	4.57%
New Jersey	5.03	-18.03%	5.72%	-19.21%	4.67%
New Mexico	2.31	-17.72%	5.97%	-18.90%	4.91%
New York	5.16	-18.07%	5.69%	-19.28%	4.61%
North Carolina	2.41	-17.68%	6.00%	-18.97%	4.85%
Ohio	5.43	-18.15%	5.63%	-19.32%	4.58%
Oklahoma	-3.47	-19.08%	4.76%	-20.74%	3.28%
Oregon	3.03	-17.83%	5.88%	-19.08%	4.76%
Pennsylvania	5.16	-18.10%	5.67%	-19.33%	4.57%
Rhode Island	-1.20	-17.48%	6.14%	-18.88%	4.89%
South Carolina	5.27	-18.06%	5.70%	-19.32%	4.58%
Texas	-1.85	-17.74%	5.91%	-19.07%	4.71%
Utah	-3.00	-18.37%	5.35%	-19.93%	3.96%
Virginia	1.08	-17.61%	6.05%	-18.89%	4.91%
Washington	4.72	-18.09%	5.67%	-19.32%	4.58%
Wisconsin	5.23	-18.13%	5.64%	-19.30%	4.60%

Table 7: CEU Results, Regional Controls

		State Policies		National Counterfactuals	
State	$\hat{\omega}$	CEU NM	CEU RF	CEU NM	CEU RF
Alabama	-2.78	11.04%	-15.31%	8.01%	-19.13%
Arizona	3.34	12.86%	-10.05%	8.74%	-18.45%
Arkansas	-3.28	8.82%	-12.62%	7.54%	-19.71%
California	-1.55	16.45%	-14.51%	8.47%	-18.15%
Colorado	-2.18	16.95%	-10.84%	8.25%	-18.39%
Connecticut	-3.08	-11.57%	-46.58%	7.76%	-19.48%
Delaware	-5.15	0.06%	-38.40%	3.47%	-25.00%
DC	3.42	5.13%	-10.04%	8.42%	-17.93%
Florida	-3.80	2.08%	-24.20%	6.77%	-21.30%
Georgia	-2.19	14.21%	-14.09%	8.24%	-18.35%
Idaho	-4.57	6.06%	-21.81%	4.96%	-22.64%
Illinois	0.89	12.84%	-13.66%	8.89%	-17.91%
Indiana	-2.97	17.77%	-12.16%	7.78%	-19.21%
Iowa	-2.03	13.39%	-8.90%	8.49%	-18.60%
Kansas	-0.89	11.25%	-9.87%	8.81%	-18.04%
Kentucky	4.57	-1.18%	-6.23%	8.53%	-18.54%
Louisiana	-0.93	-2.96%	-32.24%	8.77%	-17.99%
Maryland	-0.04	7.20%	-8.62%	8.77%	-18.00%
Massachusetts	1.17	11.47%	-26.13%	8.91%	-18.05%
Michigan	2.62	13.65%	-26.22%	8.74%	-18.39%
Minnesota	3.53	8.04%	-8.47%	8.55%	-18.41%
Mississippi	4.35	-1.87%	-6.07%	8.48%	-18.50%
Nevada	3.85	11.40%	-13.82%	8.50%	-18.44%
New Hampshire	3.43	13.12%	-13.26%	8.67%	-18.64%
New Jersey	3.61	-21.54%	-58.97%	8.57%	-18.42%
New Mexico	3.57	14.72%	-9.46%	8.59%	-18.63%
New York	3.86	-2.53%	-45.44%	8.53%	-18.53%
North Carolina	2.34	12.62%	-9.70%	8.65%	-18.34%
Ohio	3.94	14.86%	-9.31%	8.56%	-18.61%
Oklahoma	-3.97	10.51%	-14.39%	6.32%	-20.95%
Oregon	3.66	9.87%	-11.78%	8.54%	-18.72%
Pennsylvania	2.43	14.79%	-22.10%	8.78%	-18.52%
Rhode Island	0.77	12.73%	-20.45%	8.91%	-18.16%
South Carolina	4.53	12.54%	-13.88%	8.57%	-18.71%
Texas	-2.14	8.54%	-7.16%	8.20%	-18.18%
Utah	-2.81	6.67%	-7.56%	7.76%	-18.45%
Virginia	1.40	12.74%	-9.65%	8.71%	-18.10%
Washington	3.90	11.18%	-13.25%	8.49%	-18.40%
Wisconsin	3.71	15.66%	-9.62%	8.53%	-18.62%

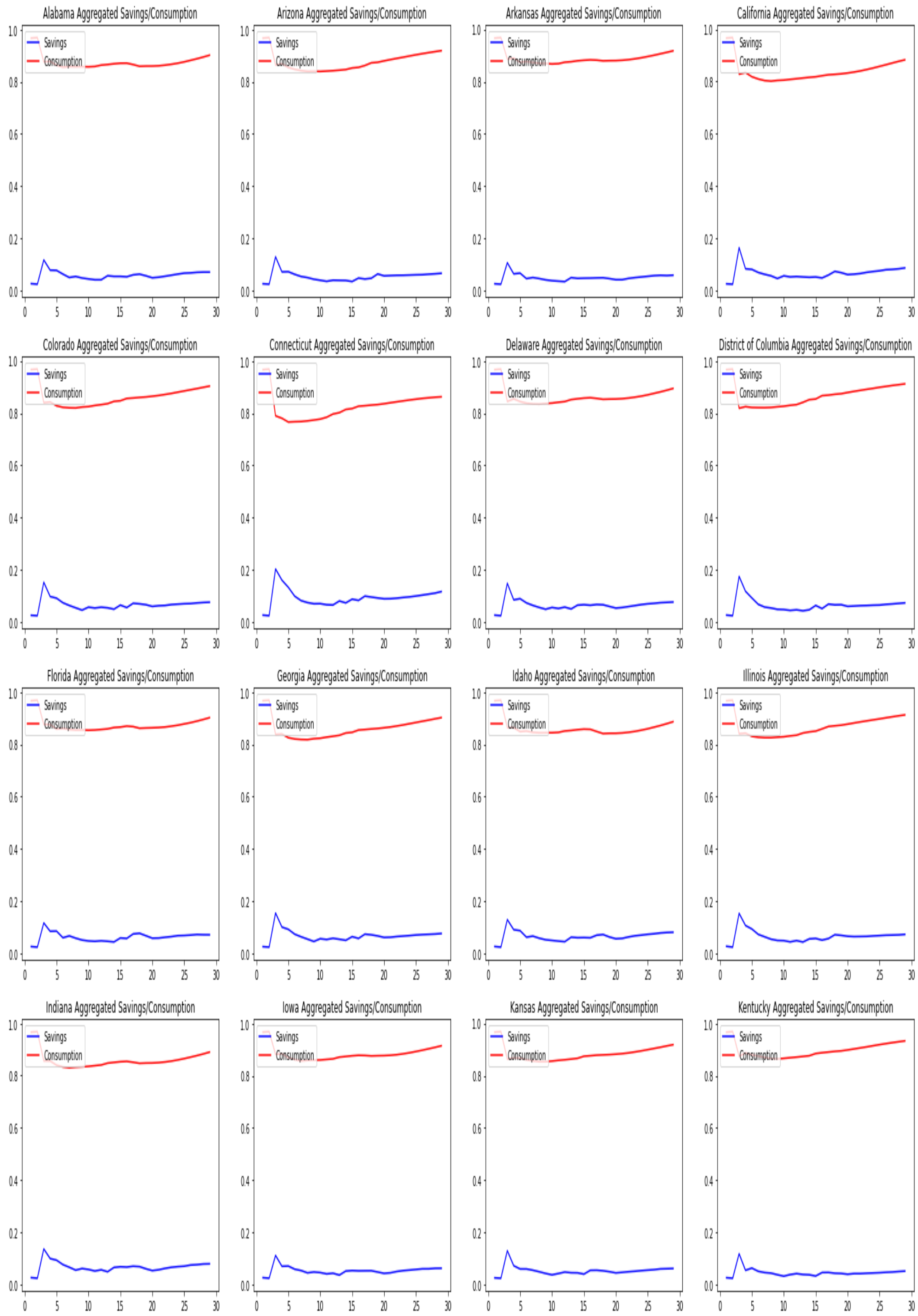
5.2 Appendix 2: β_t plots

Figure 6: Time Series of β_t by State, 16 Week Window



5.3 Household Response Functions

Figure 7: Aggregated Response Functions, Young Households, by State



Mahoney – Pandemic Response

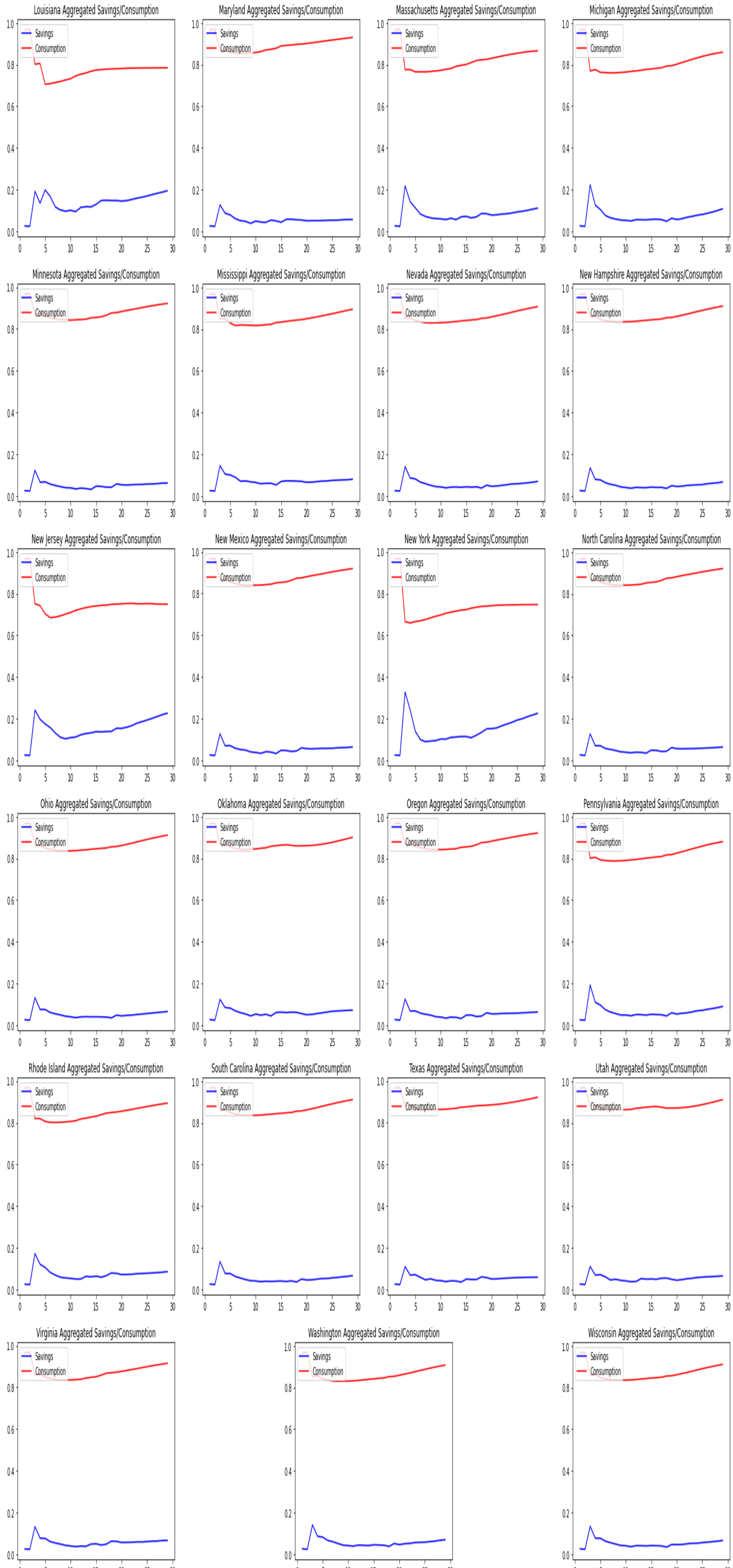
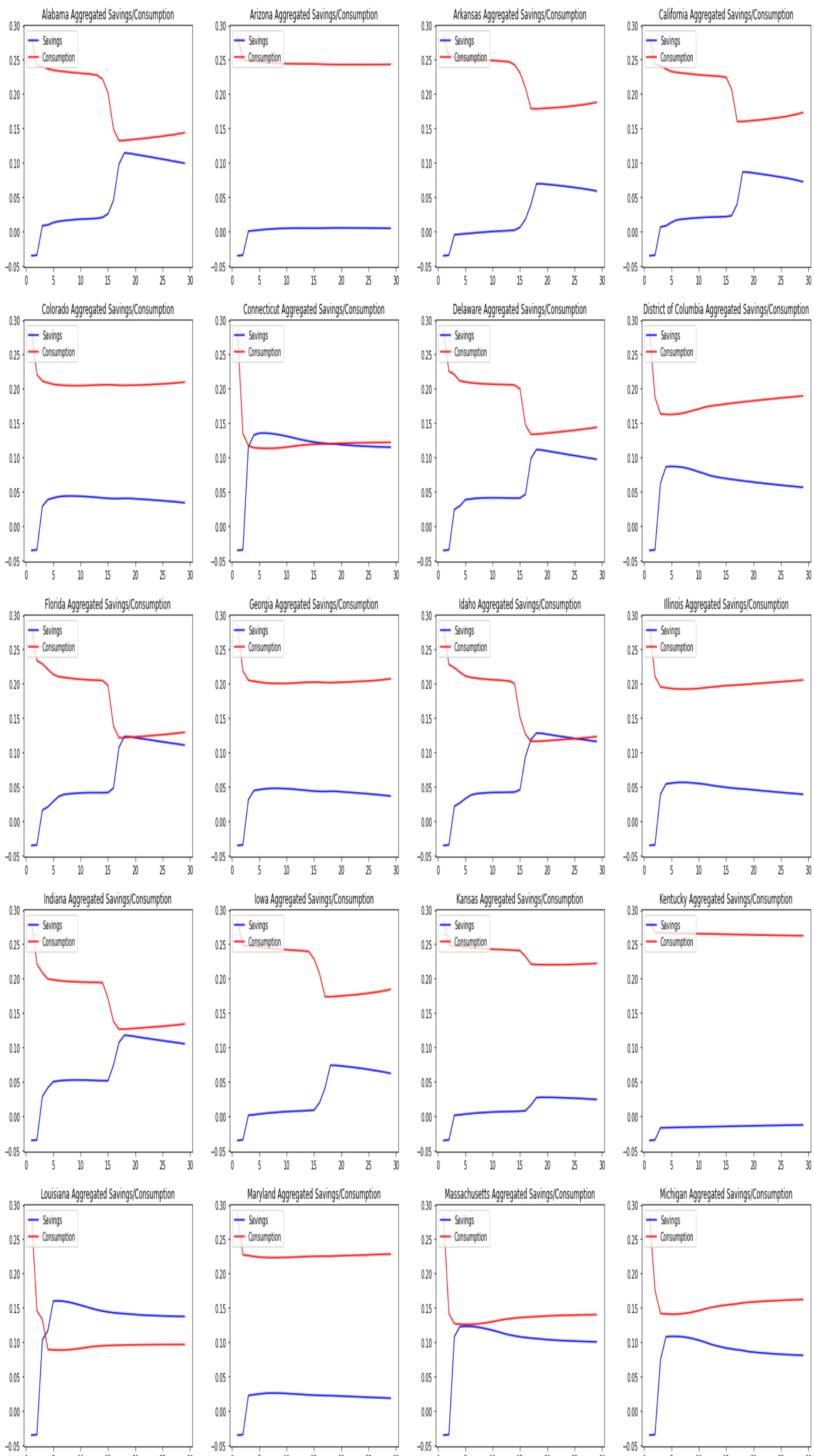
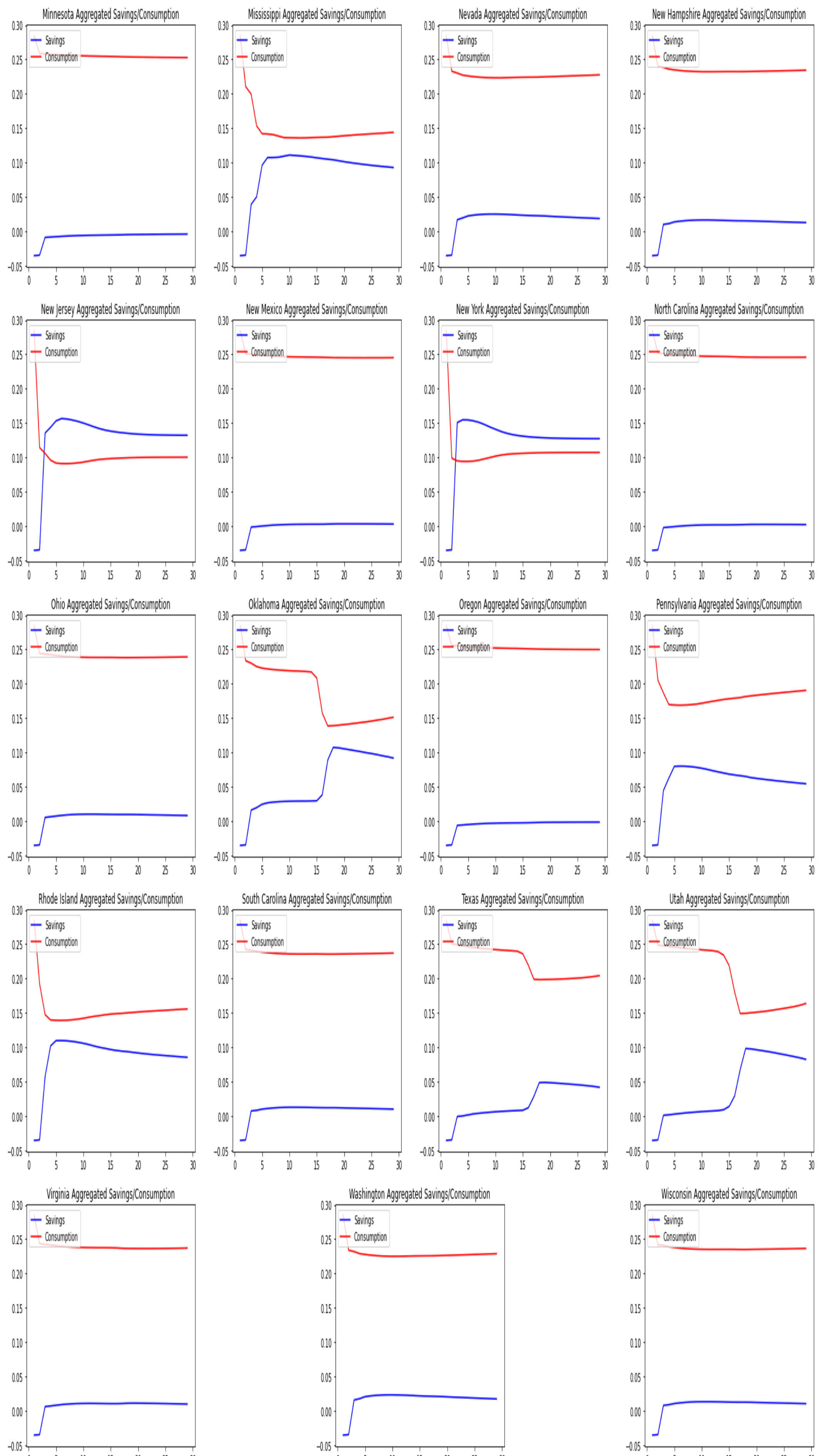


Figure 8: Aggregated Response Functions, Old Households, by State



Mahoney – Pandemic Response



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