Joint Modeling on the Impact of COVID-19 on Housing Security for Young Adults in the United States

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Abstract

As the economic repercussions due to COVID-19 unfold in the United States, stimulus and relief measures demand understanding of the pandemic's impacts. Young adults are at an elevated risk of financial vulnerability compared to other age groups, resulting in housing hardships. Combining multiple sources of data from the Census Bureau's American Community Survey (ACS) and the Household Pulse Survey (HPS), this longitudinal analysis investigates effects of COVID-19 on the probability of housing crisis among young adults under a joint modelling framework. State space model (SSM) is employed to detect the changes over time and accommodate missing values in the survey data efficiently. The proposed method explores the dynamic association between the latent class and baseline covariates including employment, broadband access, mobility, and COVID-19 cases. The constructed confidence intervals and forecasted values of homelessness help guide implementation of ongoing housing protection policies in response to COVID-19.

Keywords: State space model; Joint models; Dynamic predictions; Housing security; COVID-19 impact.

1. Introduction

The 2019 coronavirus disease (COVID-19) pandemic has not only challenged the world's healthcare systems, but also brought unexpected economic repercussions that led to the worst global recession since the financial crisis in 2008 (Nicola et al., 2020; Polyakova et al., 2020). Due to the economic slowdown and the surging unemployment figures, millions have been struggling with housing expenditures, regardless of paying rent or mortgage, causing a nationwide housing crisis (Barocas and Earnest, 2021; Nicola et al., 2020). The economic fallout of the COVID-19 pandemic disproportionately impacts groups that are financially vulnerable. Disparities in education, employment, housing and healthcare have been magnified, both as a direct result of quarantine and also indirectly due to the deteriorating macroeconomy (Barocas and Earnest, 2021; Nicola et al., 2020; Tai et al., 2020). In particular, young adults aged 18-25 in the United States are faced with heavier existing loans, lower income from wages, less job opportunities and a lack of savings (Tai et al., 2020). This is also true when assessing the current housing situation (Sills and Rich, 2021). As a result, while policies targeting the housing hardships, including the eviction moratorium, have been implemented (Sills and Rich, 2021), few made targeted considerations for young adults. Detailed data analysis is crucial for monitoring the situation and evaluating the policies.

This study aims to combine comprehensive sources to analyze factors influencing the current housing crisis and produce data products to help families and communities navigate through the current challenges. The first objective is to extract data at both the micro-level and the macro-level while incorporating different perspectives. This approach considers housing crisis both for individual households of young adults, where the main concern is to assess and predict risk of failing to paying rent or mortgage, and on the state level, where policy decisions for battling the housing crisis are made as the pandemic progressed. The second goal involves performing predictions that can utilize a continuous flow of nearly real-time data, which calls for implementing online predictions via machine learning. The COVID-19 pandemic is fast-changing, while more and more extensive data has been collected since the first wave in the beginning of 2020, making it crucial to both reflect and utilize the increasing amount and complexity of information in the modeling of housing crisis.

For this study we are interested in considering data covering the following aspects. Apart from covering different levels of data at both the micro and macro levels for individual households and different states, different social and economic topics, including both

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direct and indirect perspectives, are included in detail. For example, access to broadband connection is an indirect factor which is connected to the economic situation and geographical remoteness of the household. Also, to provide comparison in trend change and determine existing underlying influences at different stages of the pandemic, it is of interest to consider both the longitudinal progressions over a short interval as well as over a longer period of time.

The first core dataset analyzed in this study is the 2019 American Community Survey (ACS) 1-year Estimates, provided by the United States Census Bureau. ACS is an official source for nationwide information on changing socioeconomic and demographic features (United States Census Bureau, 2019). It provides a solid background on the nation and the well-being of its people, with annual estimates reporting on nearly every facet of our way of life. The Census Bureau classifies ACS into four major categories: the social category, which includes detailed and newly-introduced variables such as broadband internet access; the economic category, including employment status and health insurance; the housing category, including house ownership and occupancy; and the demographics category, including gender and education level. ACS forms a comparison with data collected during the COVID-19 pandemic. The second core dataset is the Household Pulse Survey (HPS) conducted by the Census Bureau in collaboration with the National Center for Health Statistics and other agencies, which is dedicated to investigating how the pandemic is impacting households and the livelihoods of ordinary people across the country (Centers for Disease Control and Prevention, 2019; Hermann and Cornelissen, 2020). HPS covers collects data from April 2020 at the beginning of the pandemic to the present Phase 3.1, based on a wide range of concerns including, among others, housing, transportation and food sufficiency. An interactive tool is available for quick access to HPS (Hermann and Cornelissen, 2020). While providing detailed public use data files at the weekly and household levels which includes quantitative information for food expenditure and employment in the last 7 days, HPS also covers longitudinal samples. These are samples collected over individual households repeatedly over time, allowing for further longitudinal analysis to reveal dynamic relationships and conduct online predictions. HPS has been a significant contribution to ongoing research on the impact of COVID-19 in the United States (Centers for Disease Control and Prevention, 2019). Apart from the core datasets, to reflect the COVID-19 status across the country, we incorporate the United States COVID-19 Cases and Deaths by State over Time data from the Centers for Disease Control and Prevention (CDC) to provide aggregated daily counts of COVID-19 cases and death numbers at multiple levels of geographical locations. Both confirmed and probable cases are counted. Furthermore, the COVID-19 Mobility Trends Reports from the COVID-19 Mobility Data Aggregator created by Apple adds an extra and essential perspective on transportation during the pandemic, recording volume of directions requests per geographical location based on data scrapper collected from users' devices. Effects due to different days of the week and the change of seasons need to be considered in analysis of this data.

From the integrated information represented in these data sources, we address the concern for developing an efficient model at the household level and the state level to extract information from individual households, explore dynamic connections between longitudinal variables, identify factors for increased risk of a housing crisis, and perform online predictions. We would like to better understand the housing crisis due to COVID-19 among young adults of age 18-25 and inform timely decisions. Challenges for our study come from both processing the data and implementing our objectives, which also points to several novelties of our application methods and the results. The first is conforming the four different sources of data to the same spatiotemporal scale. We then need to establish a computationally efficient framework to accommodate the increased data size due to combining multiple sources. Lastly, prediction of multi-step outcomes must be capable of incorporating updated data. We propose to adopt a joint modeling framework based on state space models (SSM) for longitudinal analysis.

The rest of the paper is organized as follows. Section 2 introduces the dynamic modeling framework based on state space models and generalized linear regression models (GLM). In Section 3, we discuss the two real-life scenarios based on the datasets, one at the individual household level and the other at the state level, to construct joint models for application. We end with discussion and remarks in Section 4.

2. Dynamic Modeling Framework

2.1 State Space Models

Our data for housing security is longitudinal in nature, with repeated measurements made over time. Since its introduction in the 1960s, the Kalman filter (Kalman, 1960) has been widely used in a diverse range of disciplines. Also known as dynamic linear models, SSMs are especially advantageous when capturing dynamic processes of longitudinal data and offer a unified methodology on a system assumed to be determined by unobserved state vectors. Durbin and Koopman (2012) provided a comprehensive introduction to this topic.

A state space model for longitudinal data assumes that,

$$\begin{aligned} \boldsymbol{y}_i(t_j) &= Z_i(t_j)\boldsymbol{\alpha}_i(t_j) + \boldsymbol{\epsilon}_i(t_j),\ \boldsymbol{\epsilon}_i(t_j) \overset{iid}{\sim} N(\mathbf{0}, H(t_j)), \\ \boldsymbol{\alpha}_i(t_j) &= T\boldsymbol{\alpha}_i(t_{j-1}) + R\boldsymbol{\eta}_i(t_j),\ \boldsymbol{\eta}_i(t_j) \overset{iid}{\sim} N(\mathbf{0}, Q(t_j)), \end{aligned} \tag{1}$$

where the $q \times 1$ vector $\boldsymbol{y}_i(t_j)$ contains q longitudinal response variables for subject i at time t_j, $i = 1, \ldots, m$ and $j = 1, \ldots, n$, $\boldsymbol{\alpha}_i(t_j)$ is a $p \times 1$ vector of latent states, $Z_i(t_j)$ is a $q \times p$ design matrix relating $\boldsymbol{y}_i(t_j)$ and $\boldsymbol{\alpha}_i(t_j)$, $\boldsymbol{\epsilon}_i(t_j)$ are random errors, T is a $p \times p$ transition matrix describing the way the underlying series moves through successive time periods, R is a $p \times p$ selection matrix, and $\boldsymbol{\eta}_i(t_j)$ is the disturbance term. For simplicity, in the remainder of this study, unless specified, we assume $R = I$. We assume that the initial distribution for the latent states $\boldsymbol{\alpha}_i(t_0)$ is $N(\boldsymbol{\mu}_0, \Sigma_0)$ for a $p \times 1$ vector $\boldsymbol{\mu}_0$ and a $p \times p$ matrix Σ_0. We also assume that observations from different subjects are independent and all subjects are observed at the same time points t_j for $j = 1, \ldots, n$. Furthermore, for simplicity we assume that $H(t_j)$ and $Q(t_j)$ are the same for all t_j. While Crevits and Croux (2019) and Ávila et al. (2018) showed that the likelihood function of a SSM is not convex, making it difficult to directly compute the MLEs for the parameters in the SSM, several different approaches to compute the MLE for parameters in SSM (1) have been discussed in details in Durbin and Koopman (2012) and Shumway and Stoffer (2009). The parameters for (1) are collected in $\Theta = (\boldsymbol{\mu}_0,\ \Sigma_0,\ T,\ Q,\ H)$.

2.2 Joint Models

To be more effective at modeling the occurrence of a housing crisis, which is a recurrent event in reality, the SSM can be joined with a GLM to create a joint modeling framework. In Section 2.2, we propose a state space approach to jointly model longitudinal variables and housing security. A thorough introduction to the joint modeling framework can be found in (Rizopoulos, 2012).

Liu and Huang (2009) proposed a joint random effects model to control the correlation between the repeated measures and the recurrent events, which were both subject to the terminal event. Alternatively, Goldstein et al. (2017) used a mixed model with splines to reflect flexibility of the longitudinal process before joining to a proportional hazards model. More relevant for our proposed state space approach is the procedure by Wang and Taylor (2001) presented a joint model also using a proportional hazards model, but with a linear Gaussian state space model instead for the longitudinal process to improve predictions of a key response indicator with high variations. We propose to remove the restrictive proportional hazards assumption and model with generalized linear regression models.

We will consider the following model for the occurrence of a housing crisis at the individual household level:

$$\rho_i(t_j)|[\boldsymbol{\alpha}_i(t_0 : t_n), \boldsymbol{x}_i(t_1 : t_n)] \sim Bernoulli(\pi_i(t_j)), \tag{2}$$

where $\rho_i(t_j)$ denotes the occurrence of a housing crisis, $\rho_i(t_j) = 1$ if the the household is unable to pay rent or mortgage in the given week and 0 otherwise, $\boldsymbol{\alpha}_i(t_0 : t_n)$ is the $p \times 1$ latent state vector at time points t_0 to t_n, defined as in (1), $\boldsymbol{x}_i(t_j)$ is the vector of regression covariates as defined for the parameters of (1), $\pi_i(t_j) = logit(P(\pi_i(t_j) = 1))$, and $\pi_i(t_j)$ is modeled by the latent states and regression covariates in the following way:

$$logit(\pi_i(t_j) = \boldsymbol{x}_i(t_j)'\gamma_{11} + \boldsymbol{\alpha}_i(t_j)'D_1\gamma_{12}, \tag{3}$$

where γ_{11}, γ_{12} are parameter vectors, D_1 is the design matrix. As this is a logistic regression, (2) represents the random component of the GLM and (3) specifies the link function and the systematic component.

Furthermore, at the state level, we will consider the following model for the proportion of surveyed households facing a housing crisis in the state:

$$h_i(t_j)|[\boldsymbol{\alpha}_i(t_0:t_n), \boldsymbol{x}_i(t_1:t_n)] \sim Binomial(\xi_i(t_j)),\ s_i(t_j) = \frac{h_i(t_j)}{m} \tag{4}$$

where $s_i(t_j)$ is the proportion of households experiencing a housing crisis in the state, $h_i(t_j)$ is the total number of households during a housing crisis in the state in the given week, $s_i(t_j) = 0, \frac{1}{m}, \ldots, 1$, $\xi_i(t_j) = logit(P(\rho_i(t_j) = 1))$, modeled by the latent states and regression covariates in the following way:

$$logit(\xi_i(t_j)) = \boldsymbol{x}_i(t_j)'\gamma_{21} + \boldsymbol{\alpha}_i(t_j)'D_1\gamma_{22}, \tag{5}$$

where γ_{21}, γ_{22} are parameter vectors, D_2 is the design matrix. (4) represent the random component while (5) specifies the link function and the systematic component.

3. Applications

3.1 Scenario I: Individual Households, Early Stage Response

For application of the proposed joint modeling framework, in the first application we consider the beginning of the pandemic when little information was collected and it was critical to identify individual households of young adults experiencing or at risk of a housing crisis to provide targeted and timely relief measures or social support. We consider one longitudinal variable, household money spent in last 7 days on food, from HPS as $y_i(t_j)$, for $i = 1, \ldots, 55$ for different households of young adults aged 18-25 across the country and $j = 1, 2, 3$ for surveyed weeks from 05/06/2020 to 05/26/2020 in Phase I of the survey. We select household expenditure for food as the longitudinal response for the state space model because food sufficiency is affected in households experiencing housing crisis. The connection is often mutual, making food expenditure one of the ideal indicators for housing crisis.

We select a total of 7 covariates over a wide range for $\boldsymbol{x}_i(t_j)$. We choose gender (Male vs. Female) and education level (Bachelor's or above vs. others) from HPS. For the state of residence for the household, we select the percentage of households with broadband access, percentage of occupied households, and percentage covered by health insurance from ACS 2019. In addition, we consider number of new weekly COVID-19 cases in each state from CDC and relative volume of direction requests from Apple mobility data as the last two covariates. In Figure 1, we randomly select five households and display the money spent on food for each week at the early stage of the pandemic from HPS.

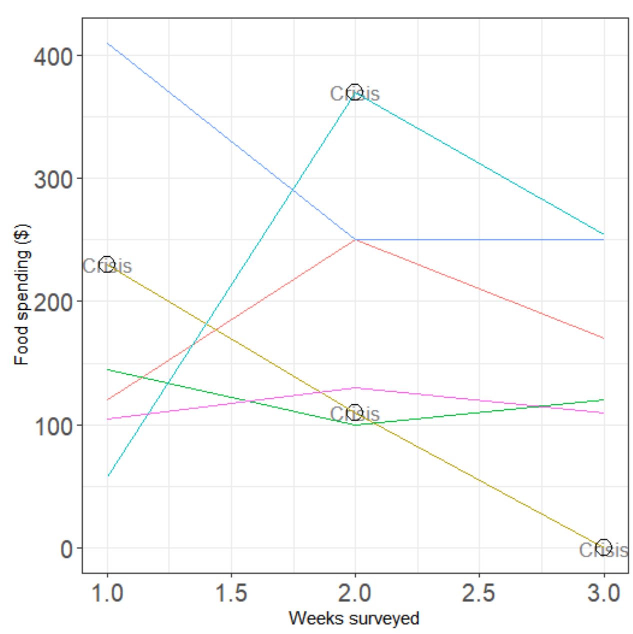

Figure 1: Household money spent in last 7 days on food, 5 randomly selected households.

Any response of failure to pay rent or mortgage from households of young adults is classified as a housing crisis in the reported week. After plotting the housing crisis faced by each household, one stands out as a special case for concern, experiencing housing crisis on a weekly basis throughout the survey period. The unexpectedly common occurrence and persistence of housing crisis is a strong indicator that the situation is severely underestimated.

We illustrate the online prediction capabilities of the proposed methods in Figure 2, where uncertainty increases due to forecasting further into the future. For a randomly selected individual household, the filtering estimates of longitudinal trajectories of household weekly food expenditure from the state space component of the joint modeling framework is plotted as lines. The dynamic estimates of the food expenditure two weeks into the future is shown as the extension, with shaded confidence intervals. When only two weeks of data have been collected in HPS at the beginning of the project, the forecast reflected an upward trend, but with the additional consideration of the third weekly response results, the predicted food expenditure is altered significantly. The new downward trend indicates that the current state space model has successfully considered the new information. This highlights the effectiveness of the proposed modeling framework in incorporating updated survey results as the pandemic develops. As more information becomes available, the online prediction model has the benefit of providing more accurate predictions of longitudinal variables. Apart from the improving accuracy, the advantage of this approach also includes that research analysis may be conducted on longitudinal survey data much earlier compared to other models which would require waiting for the entire survey period to be completed before starting.

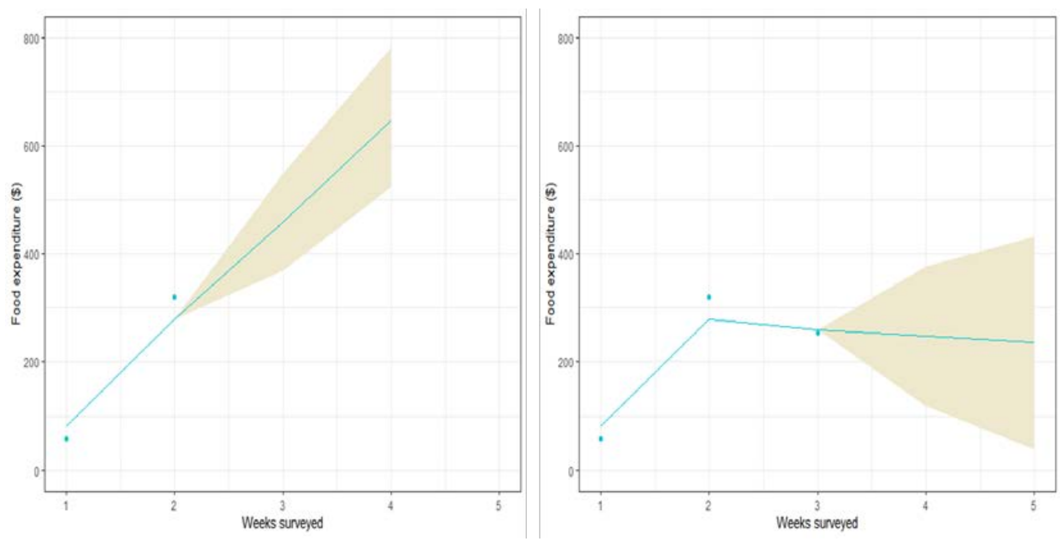

Figure 2: Filtering estimates of longitudinal trajectories of household money spent in last 7 days on food for a randomly selected household. Dots: observed values, lines: filtering estimates, extended lines: the dynamic estimates of the food expenditure for two weeks following the last observed week, shaded region: confidence interval.

Furthermore, the probability of housing crisis occurring in the upcoming fortnight for each week is modeled by the GLM in (2) and (3), and we show the updates for this probability over three consecutive weeks in Figure 3. For the selected individual household of young adults, the probability is relatively low and maintains a decreasing trend. In this first scenario, our proposed joint modeling framework has been applied to forecast risk of housing insecurity both directly and indirectly for individual households in the United States based on a limited amount of data at the beginning of the pandemic, to act as a ready-to-use online prediction model to identify households at risk of housing crisis.

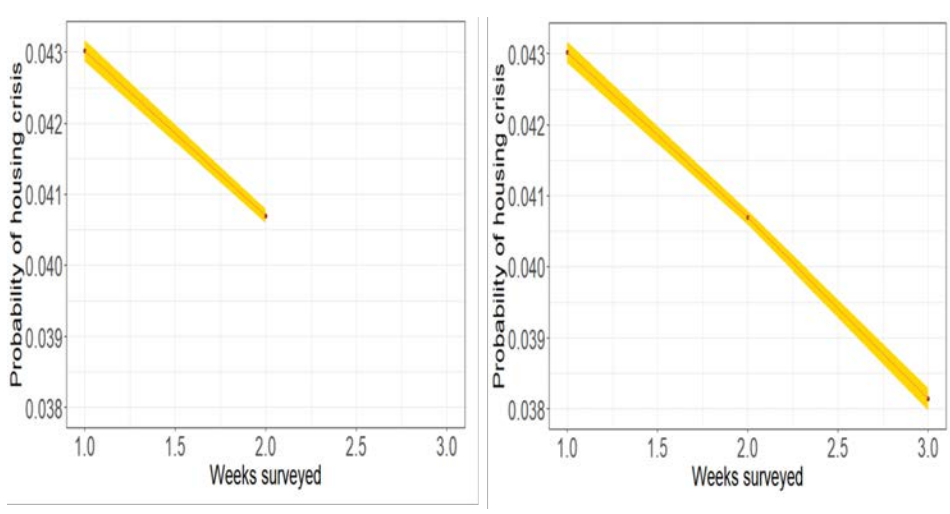

Figure 3: The estimated probability for housing crisis occurring in the next two weeks shown in dots with the confidence bound plotted as the shaded region.

3.2 Scenario II: States, Online Prediction

In the second application, we consider the situation where the pandemic has been ongoing for several months, where sufficient data were collected and the goal is to make informed decisions at the state level regarding housing crisis. We consider two longitudinal variables, the average of money spent in last 7 days on food by households of young adults and the proportion of young adults employed among surveyed in each state from HPS Phase I as $\boldsymbol{y}_i(t_j)$, for $i = 1, \ldots, 51$ for different states and $j = 1, \ldots, 12$ for surveyed weeks from 04/23/2020 to 07/21/2020. We again select a total of 7 covariates for $\boldsymbol{x}_i(t_j)$, with more variables as percentages and proportions. We choose percentage of male respondents within state (Male vs. Female) and proportion of respondents with a degree of Bachelor's or above vs others from HPS. From ACS 2019, we select the percentage of households with broadband access, percentage of occupied households, and percentage covered by health insurance for each state. In addition to the number of new weekly COVID-19 cases in each state from CDC, we include the state average of relative volume of direction requests from Apple mobility data.

In Figure 4, we find significant variations in the employment status for each of the 5 randomly selected states, over the span of 12 weeks. The employment status is based on respondents in HPS. In particular, Alaska started off with an alarming percentage of employed young adults below 30% in April 2020 when the chaotic effects of the pandemic was in full scale, and recovered quickly to become the state with the highest employment status among the five states at the end of the period. Illinois, on the other hand, started as the state with the highest percentage of employed young adult respondents and fell to the lowest at the end. These details from HPS provide a unique perspective on the economic situation throughout the pandemic and offer great potentials for future research.

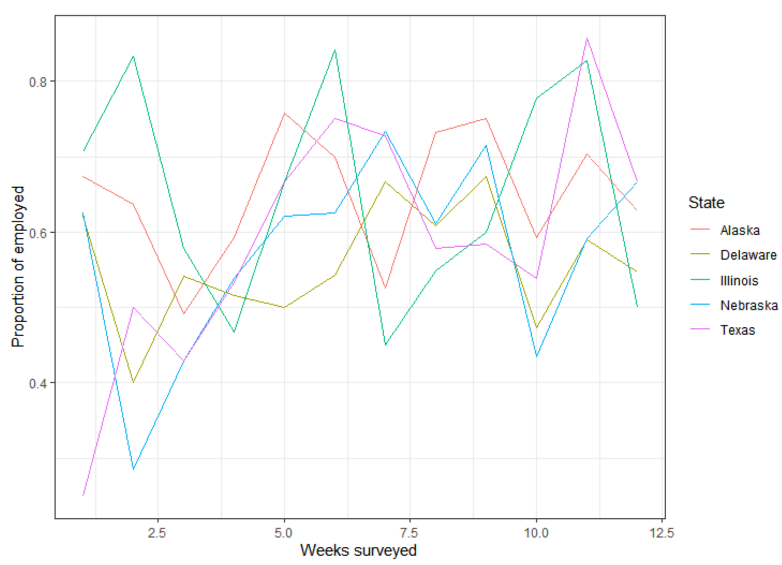

Figure 4: Employment status for 5 randomly selected states.

We illustrate the average weekly food expenditure of households in five randomly selected states in Figure 5. A sharp increase in food expenditure in Texas around the week of 5/26/2020 is of interest, reflecting how basic needs like food security can be also unexpectedly more vulnerable under the pandemic. Therefore, we propose and implement a more effective and accurate online prediction due to a richer collection of longitudinal data over time, to assist decision making for battling the economic repercussions of COVID-19 at the state level.

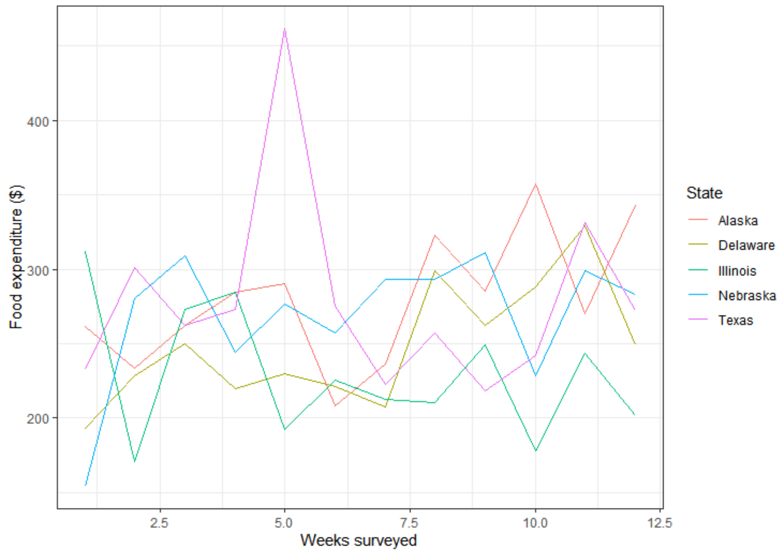

Figure 5: Average of household money spent in last 7 days on food, 5 randomly selected states.

The online prediction of the proportion of employed young adults for the state of California is carried out in Figure 6. We consider the situation where the prediction is first conducted based on eight weeks of collected data, and forecasts are made for six consecutive weeks into the future. Then at this time point, the predicted proportion of employed for the following Week 9 to Week 14 forms an upward trend. Then when the data from Week 9 becomes available, the prediction from the proposed modeling framework at the previous time point proved to be very accurate. The prediction is updated to cover Week 10 to Week 15, maintaining the general upward trend. Furthermore, the confidence bounds depicted by the shadowed regions increases as the forecast is further into the future, reflecting greater uncertainty. The procedure continues until the last observed week in Phase I, the week of 07/21/2020, with effective forecasts into September of 2020, providing a reliable and extended forecast for employment statistics within the state by considering influences from COVID-19 as well as an ensemble of selected covariates such as the education level of young adults and housing information.

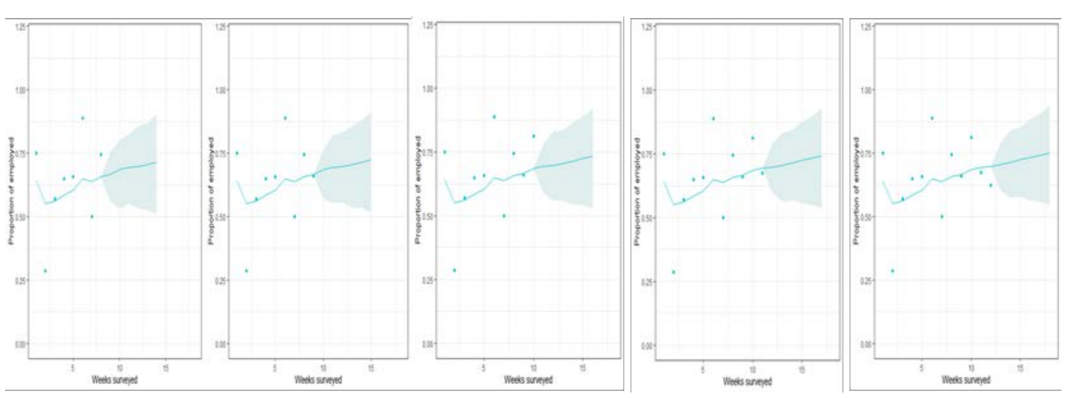

Figure 6: Filtering estimates of longitudinal trajectories of proportion of employed for California. Dots: observed values, lines: filtering estimates, extended lines: the dynamic estimates of proportion of employed for six weeks following the last observed week, shaded region: confidence interval.

We can also make online predictions for the average weekly household food expenditure of young adults in California. In Figure 7, we again start predictions based on eight weeks of data and construct six weeks of forecast. The predicted food expenditure is consistently going up based on data up to Week 8, raising concerns for increased hardship for households due to food insecurity in the near future. Food industry was heavily impacted by quarantine, and as a result food shortages have frequently occurred at the beginning of the pandemic (Mead et al., 2020; Huang et al., 2021). Labor shortages and limited shiptments further contributed to higher food prices (Melo, 2020; Huang et al., 2021). Our findings also project that food expenditure per week per household may increase by as much as one hundred dollars in just three months, placing a considerable financial strain on most households of young adults. This helps quantify the urgency for immediate relief effort in the state of California.

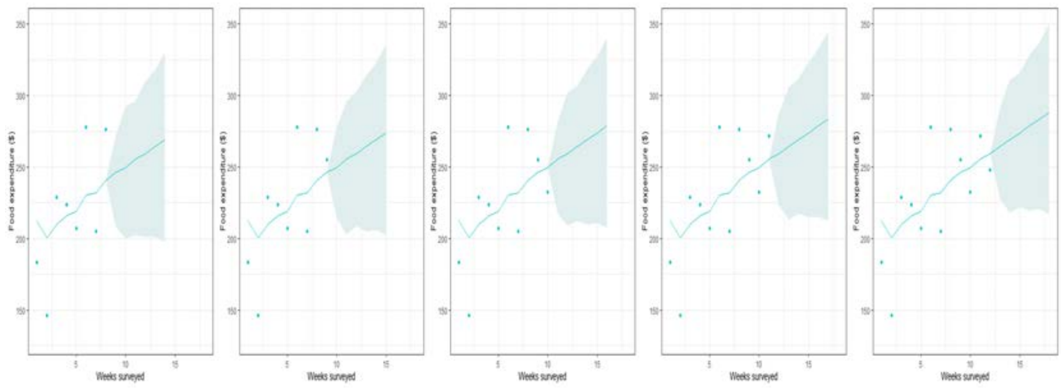

Figure 7: Filtering estimates of longitudinal trajectories of average of household money spent in last 7 days on food for California. Dots: observed values, lines: filtering estimates, extended lines: the dynamic estimates of average food expenditure for six weeks following the last observed week, shaded region: confidence interval.

The overall housing crisis risk at the state level is modeled in Figure 8 as the estimated proportion for housing crisis six weeks into the future. This proportion is based on how many of California's households of young adults may experience failure to keep up with either rent or mortgage payments. The variations suggest that risk for housing insecurity for young adults in California may increase significantly in just one or two weeks. This suggests that relief efforts requiring a longer time period to enforce, such as tax returns, may not be sufficient for addressing housing insecurity in a timely manner, and should be accompanied by policies such as eviction moratoriums.

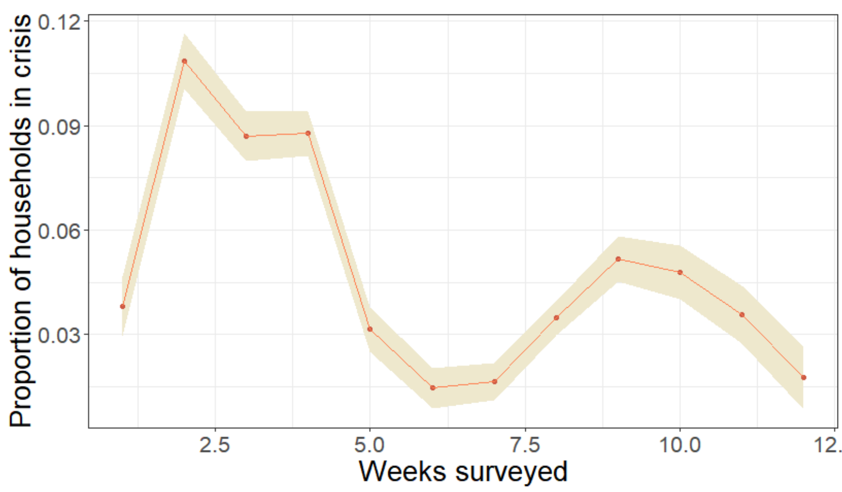

Figure 8: The estimated proportion for housing crisis six weeks into the future for California shown in lines, with the confidence bound plotted as the shaded region.

4. Discussion

In this study, we proposed and implemented a novel joint modeling framework utilizing state space models and generalized linear regressions to dynamically model the impact of COVID-19 on housing security for households of young adults and make online predictions on risks of housing crisis, at both the household level and the state level. The findings not only corroborate with different studies on economic impacts of COVID-19, but also provides details to help both families and officials make crucial decisions on battling housing hardships throughout the pandemic. Findings also supplement housing analysis from the HPS interactive data tool. Based on the proposed method, we are currently developing a dynamic modeling data tool to be made publicly available such that individuals may use it to make informed decisions on their own housing situation. The current joint modeling framework may be extended to include more variables to better utilize the wealth of information available from ACS and HPS. As the core data sources for this study, ACS and HPS have proven to be extremely valuable and effective resources for comprehensive analysis of COVID-19 impact on the U.S., and shows potential for further research on this topic. We would like to conduct research to incorporate these two resources and additional data tools from The Opportunity Project in the following months on a more challenging data scale.

References

Barocas, J. A. and M. Earnest (2021). The urgent public health need to develop "crisis standards of housing": lessons from the COVID-19 pandemic. *American Journal of Public Health 111*(7), 1207–1209.

Centers for Disease Control and Prevention (2019). Novel COVID-19 survey takes nation's social, mental "pulse". Accessed: March 30, 2021.

Crevits, R. and C. Croux (2019). Robust estimation of linear state space models. *Communications in Statistics - Simulation and Computation 48*(6), 1694–1705.

Durbin, J. and S. J. Koopman (2012). *Time series analysis by state space methods*, Volume 38. Oxford University Press.

Goldstein, B. A., G. M. Pomann, W. C. Winkelmayer, and M. J. Pencina (2017). A comparison of risk prediction methods using repeated observations: an application to electronic health records for hemodialysis. *Statistics in Medicine 36*(17), 2750–2763.

Hermann, A. and S. Cornelissen (2020). Using the Census Bureau's Household Pulse Survey to assess the economic impacts of COVID-19 on America's households. Accessed: March 2, 2021.

Huang, K. M., A. C. Sant'Anna, and X. Etienne (2021). How did covid-19 impact us household foods? an analysis six months in. *PLoS One 16*(9).

Kalman, R. E. (1960). A new approach to linear filtering and prediction problems. *Journal of basic Engineering 82*(1), 35–45.

Liu, L. and X. Huang (2009). Joint analysis of correlated repeated measures and recurrent events processes in the presence of death, with application to a study on acquired immune deficiency syndrome. *Journal of the Royal Statistical Society, Series C 58*, 65–81.

Mead, D., K. Ransom, S. B. Reed, and S. Sager (2020). The impact of the covid-19 pandemic on food price indexes and data collection. *Bureau of Labor Statistics Monthly Lab Review*.

Melo, G. (2020). The path forward: Us consumer and food retail responses to covid-19. *Choices 35*(3).

Nicola, M., Z. Alsafi, C. Sohrabi, A. Kerwan, A. Al-Jabir, C. Iosifidis, M. Agha, and R. Agha (2020). The socio-economic implications of the coronavirus pandemic (COVID-19): A review. *International journal of surgery 78*, 185–193.

Polyakova, M., G. Kocks, V. Udalova, and A. Finkelstein (2020). Initial economic damage from the COVID-19 pandemic in the United States is more widespread across ages and geographies than initial mortality impacts. *National Academy of Sciences 117*(45), 27934–27939.

Rizopoulos, D. (2012). *Joint models for longitudinal and time-to-event data: With applications in R*. Chapman and Hall/CRC.

Shumway, R. H. and D. S. Stoffer (2009). An approach to time series smoothing and forecasting using the em algorithm. *Journal of Time Series Analysis 3*, 253–264.

Sills, S. J. and B. A. Rich (2021). Housing instability and public health: implications of the eviction moratoria during the COVID-19 pandemic. *North Carolina Medical Journal 82*(4), 271–275.

Tai, D. B. G., A. Shah, C. A. Doubeni, I. G. Sia, and M. L. Wieland (2020). The disproportionate impact of COVID-19 on racial and ethnic minorities in the United States. *Clinical Infectious Diseases 72*(4), 703–706.

United States Census Bureau (2019). Comparing ACS data. Accessed: March 10, 2021.

Wang, Y. and J. Taylor (2001). Jointly modeling longitudinal and event time data with application to acquired immunodeficiency syndrome. *Journal of the American Statistical Association 96*(455), 895–905.

Ávila, F., J. Yuz, A. Donaire, and J. Agüero (2018). Constrained maximum likelihood estimation for state space sampled-data models. pp. 621–626.