Social Determinants Relating to Covid-19 Infection Risk, Vaccination Rates, and Telehealth Utilization

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Background

The COVID pandemic has highlighted the real impacts of social determinants of health (SDoH) on health risks and outcomes. Studies have found that African Americans, Latino individuals, and Native Americans have experienced a disproportionate burden of COVID-19-related infections and deaths (Price-Haygood Burton 2020, Andrasfay Goldman 2021). Further, numerous reports have shown that Black, Latinos, and Native Americans are least likely to receive the COVID-19 vaccination (Cuellar NG). Since, Alaska is a unique state culturally, demographically, and environmentally, and social factors can influence population health at various spatial scales, an investigation into Covid-19 risk and vaccination at the Alaskan Community Health Center (CHC) level is merited.

By coupling risk stratification (i.e., the separation of patients into high risk and low risk populations) with interventions that target high-risk groups, health care systems can be improved. Auxiliary data regarding a patient's environment and socio-economics can be used to inform risk stratification algorithms, which can be used to improve the accuracy of diagnosis, which can in-turn lower health care costs and improve patient outcomes. In the State of Alaska, 12/26 CHCs use the software application Azara DRVS (henceforth DRVS) for data-driven analytics, quality measurement, and reporting. Currently, these health centers use a use an algorithm built into DRVS to assess Covid related risk. By taking additional social determinants into account, this algorithm can likely be improved.

In this project, we will use a statistical technique called survival analysis to synthesize up-to-date Covid-19 related information and identify factors that place CHC patients at an increased risk of contracting the Covid-19 infection. A proportional hazards model will be used to measure patient risk. A statistical technique called logistic regression was also used to identify potential factors influencing telehealth access. This information was used to identify patient populations that have been utilizing telehealth services.

The COVID-19 pandemic has accelerated the adoption of telehealth services in the State of Alaska. Since Alaska has many remote areas, the state's telemedicine definitions are generally broader than in other states. Formally, the State of Alaska defines telemedicine as "… the transfer of medical data through audio, video, or data communications engaged in over two or more locations between providers who are physically separated from the patient and from each other." Telemedicine can be utilized using different modes of delivery including interactive video, store-and-forward methods, and self-monitoring applications. Unlike many other states, Alaska's Medicaid program covers many different types of telemedicine (video, store-and-forward, and remote patient monitoring). A telemedicine parity law is currently proposed for legislation. Under Alaska telehealth law, mental health services delivered over telemedicine must be covered by private payers.

The results of this study were used to evaluate the effectiveness of telehealth services in treating patients with increased Covid-19 related risk. This information will help policy makers as they evaluate the utility of telehealth services and image the future of telehealth in the State of Alaska. The results of this study were also used to make recommendation for how the risk stratification algorithm in DRVS can be modified to more accurately reflect Covid-19 related risk.

Objectives

The objectives of this study are to:

1: Estimate the probability that a patient from a given patient population has not contracted the Covid-19 infection at any given point in time and identify factors associated with increased Covid-19 infection risk.

2: Estimate the probability that a patient from a given population has not received a Covid-19 vaccination at any point in time and identify factors associated unvaccinated populations.

3: Estimate the probability that a patient from a given patient population has utilized telehealth services in the past month and identify factors affecting telehealth utilization.

Data Reduction

A person's health is affected by a number of social determinants. This includes individual factors such as who they are (age, sex, and genetic factors). This also includes behavioral factors such as what they do (diet, physical activity, and drug use). Health is also affected by conditions in which people are born, grow, live, work, and age. These include social and community networks; socio-economic, cultural, and environmental conditions; and health systems. In this analysis we considered, 10 different predictors of health (i.e., explanatory variables). The measures considered are detailed in the Table 1.

Patient Level Data Analyzed

Variable Description	Variable Type
Was the patient diagnosed with a new case of Covid-19 during the encounter (Yes or No)	Response
Was this a telehealth appointment (Yes or No)	Response
If this was a telehealth appointment, what was the modality (Telephone, video, ...)	Response
Health center where the encounter occurred	Explanatory
Patient's age	Explanatory
Patient's sex	Explanatory
Patient's race	Explanatory
Patient's ethnicity	Explanatory
Patient's language	Explanatory
Patient's insurance category (Uninsured, Medicaid/Medicare, ...)	Explanatory

Does the patient have an active depression diagnosis during the study period (Yes or No)	Explanatory
Did the patient identify as a tobacco user in the past 24 months (Yes or No)	Explanatory
Was the patient identified as being an unhealthy alcohol user during the past 24 months (Yes or No)	Explanatory

Table 1: Information to be downloaded from DRVS, de-identified, cleaned, and analyzed this study.

In this analysis, 21 months of data ranging from 01/12/2020 to 10/31/2021 taken from 10 health centers spread across the state were considered.

Data Analysis

An extension of the usual proportional hazards model was used to identify patient populations that are at increased risk of being infected with the Covid-19 virus (Rodríguez 2007) and identify factors associated with increased vaccination rates. In developing the statistical framework of the model, we will start by defining the hazard and survival functions in discrete time.

Let T be a discrete random variable representing the month in which patient receives a positive Covid-19 diagnosis. Here, T takes the values $t_1 < t_2 < \cdots$ with probabilities $f(t_j) = f_j = \Pr(T = t_j)$. The "survival function" is defined at time t_j as the probability that the time of infection T is at least t_j:

$$S(t_j) = S_j = \Pr(T \geq t_j) = \sum_{k=j}^{\infty} f_j.$$

Next, the hazard function λ_j is defined at time t_j as the probability of being diagnosed with a Covid-19 infection at that time given that the individual has not been infected up until that time.

We now let $i \in \{1,2,\cdots,n\}$ be an index representing the patient. In this study, we will consider the patient population to be the set of all patients with any meaningful contact between the patient and a health center in the time duration considered in this study. Additionally, we let x_i be a vector representing the health determinants (i.e., explanatory variables) detailed in Table 1. The proportional hazard model is now defined as

$$\text{logit}\lambda(t_j|x_i) = \alpha_j + x_i^T \beta.$$

In this equation, $\alpha_j = \text{logit}\lambda_0(t_j)$ where $\lambda_0(t_j)$ is the baseline hazard. The baseline hazard function is analogous to the intercept term in a multiple regression or logistic regression. β reflects the effect of each determinant of health on the logit of the baseline hazard. The hazard ratio, $\lambda(t_j|x_i)/\lambda_0(t_j)$ is regarded as the relative risk that patient i is infected with the Covid-19 virus at time j.

Logistic regression was used to assess which patient populations have been utilizing telehealth services. Letting $Y_{ij} = 0$ be the event that the i^{th} appointment was an in-person encounter, and letting $Y_i = 1$ be the event that the i^{th} appointment was a telehealth encounter, the probability that the i^{th} patient utilized telehealth services was modeled as

$$\text{logit}p_i = \alpha + x_i^T \beta.$$

β reflects the effect of each variable on probability of telehealth utilization. Separate models were fit for each and every subset of explanatory variables listed in Table 1, and AIC was used as the model selection criterion. The most complex models were favored in the variable selection procedure. Ultimately, we considered the saturated models (with all of the explanatory variables listed in Table 1).

Results

Covid-19 Infection Risk

Covid-19 infection rates peaked July 2021. More Covid-19 new cases have been documented in September 2021 than in any other month on record. During this month, 2.6% of patients that entered a health center in September were diagnosed with a new case of Covid-19 (Figure 1). Right now, approximately 95% of patients visiting community health centers have not received a positive Covid-19 diagnosis (Figure 2). Of the predictor variables that we considered, the health center (a proxy for a patient's geographic location) was found to have the greatest effect upon a patients Covid-19 infection risk. Native Alaskans were identified as the racial group with the greatest Covid-19 risk of infection. We also found differences in Covid-19 infection rates between ethnicities. Hispanic patients were found to have lower infection rates than non-Hispanics. Patients between the ages of 20 and 60 had slightly elevated infection rates compared to patients from other age classes. A patient's language and sex did not have a meaningful impact on Covid-19 infection rates.

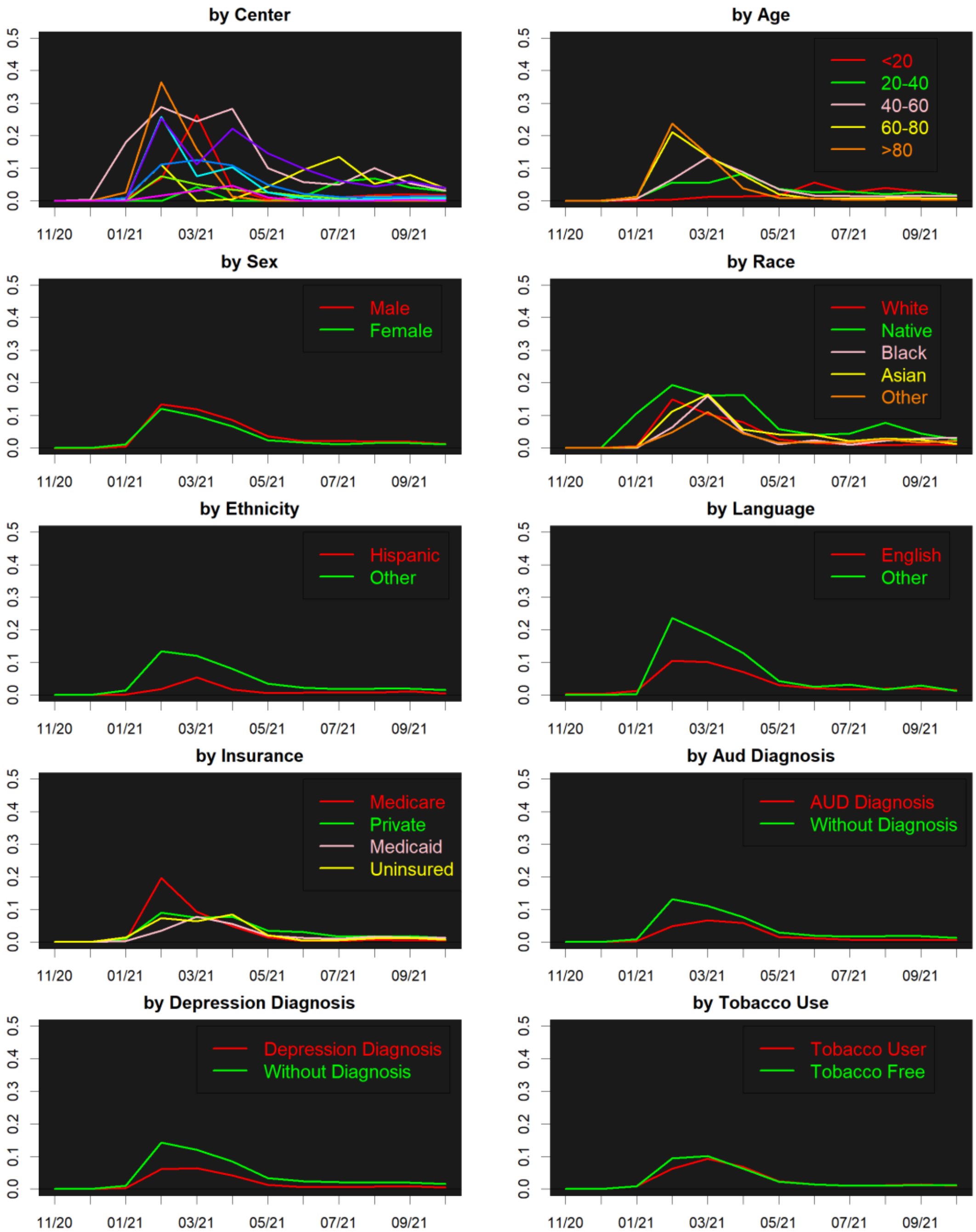
Covid-19 Vaccination Rates

In the 10 health centers that we considered, the rates of vaccine administration peaked in February 2021. While there was a significant amount of variation between health centers, approximately 15 percent of patients that encountered by a health center in February 2021 were given a Covid-19 vaccination. Rates of vaccine administration have decrease since February 2021 despite the surge in Covid cases that occurred in July 2021. Right now, approximately 80 percent of patients encountered by a health center have been immunized by the health center. Age was found to have a significant effect on vaccine administration. Older patients have been immunized at greater rates compared to younger patients. Patients on Medicare have been immunized at greater rates compared to patients with other types of insurance.

Telehealth Utilization

The utilization of telehealth services peaked in April 2020. Since this time, the utilization of these services has declined at a steady rate. Approximately 10 percent of all patient encounters occurred by telehealth in November 2021. For the patient level variables considered in this analysis, depression status was found to have the greatest effect on telehealth utilization. Patients with active depression diagnosis were more likely to utilize telehealth services that patients without depression diagnosis. A patient’s insurance class was the next most influential patient level variable on predicting telehealth utilization. We found that telehealth utilization rates were highest for uninsured and those on Medicaid. Additionally, patients between the ages of 20 and 60 were found to utilize telehealth the highest rates. Whites and natives were also found to utilize telehealth services at higher rates. Females were slightly more likely than males to utilize telehealth services. The parameters that we estimated are detailed further in Table 2.

Figures and Tables



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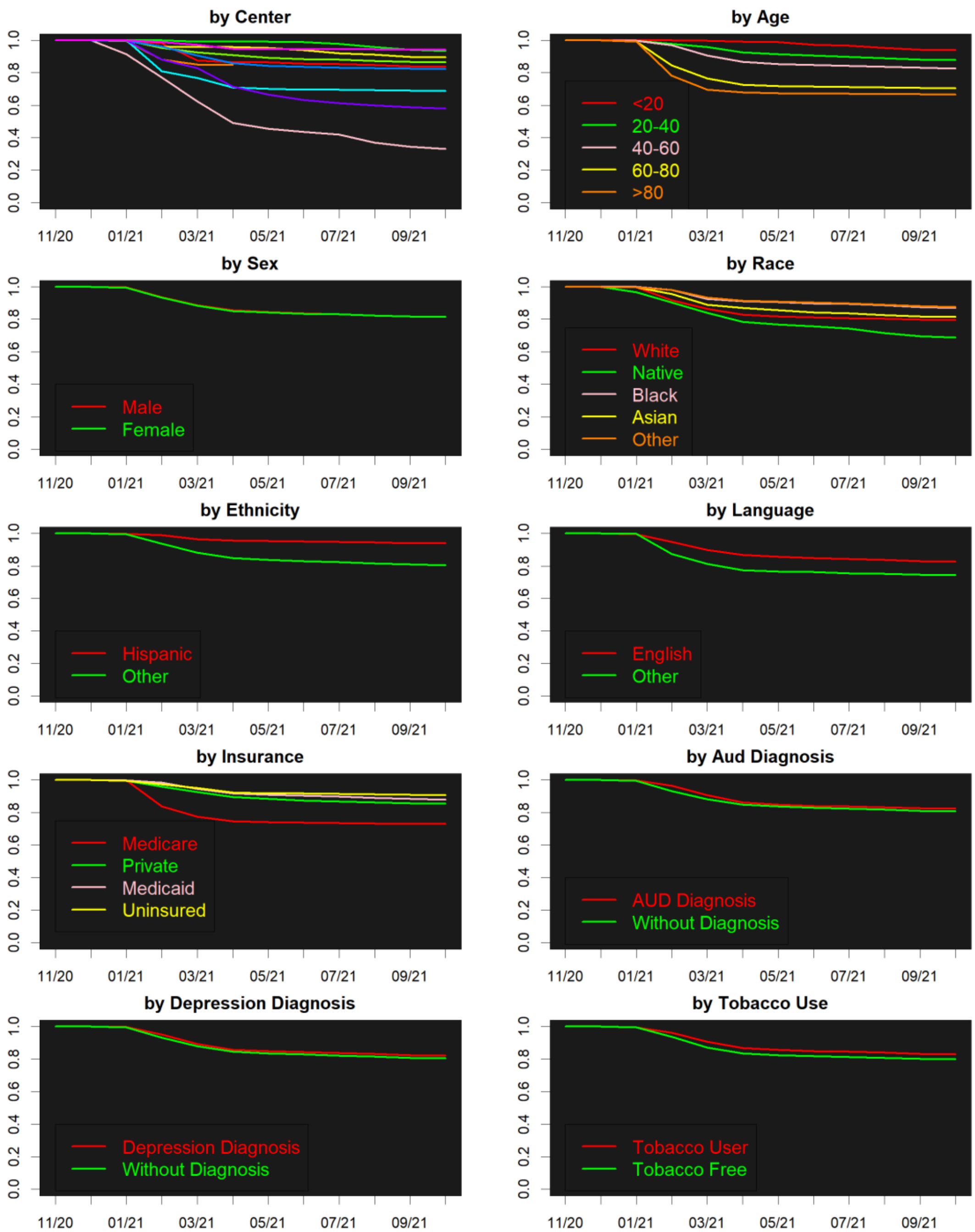
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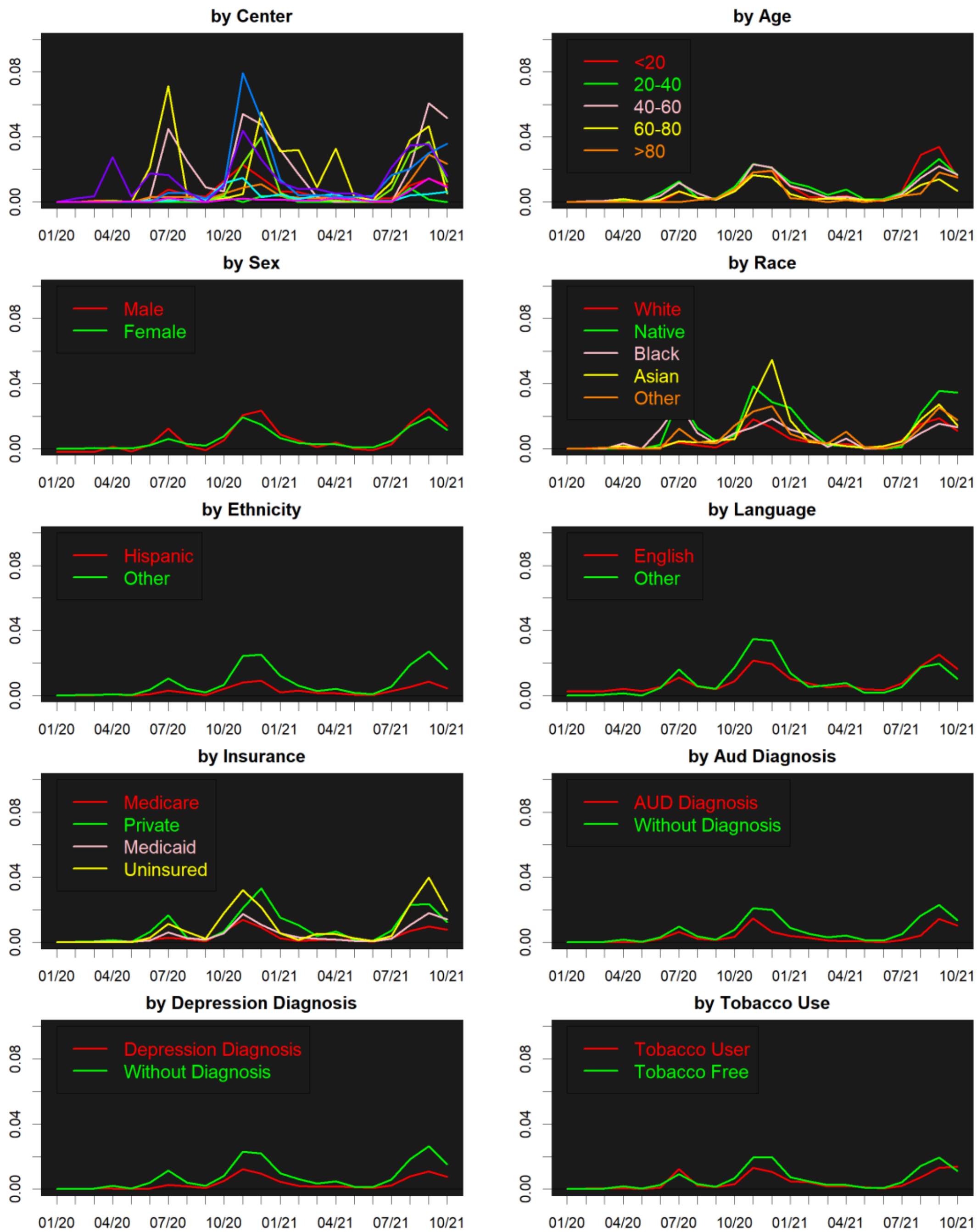

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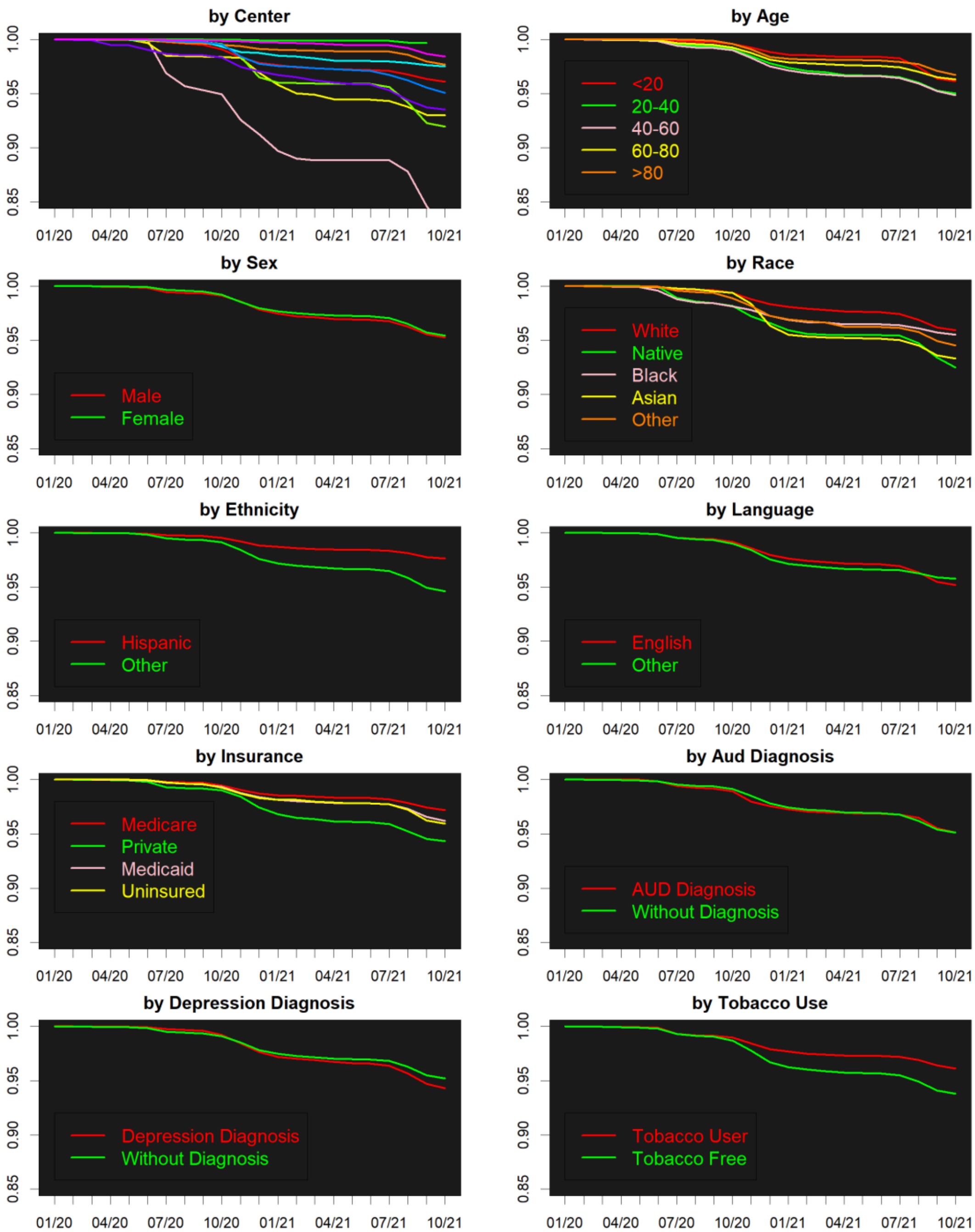

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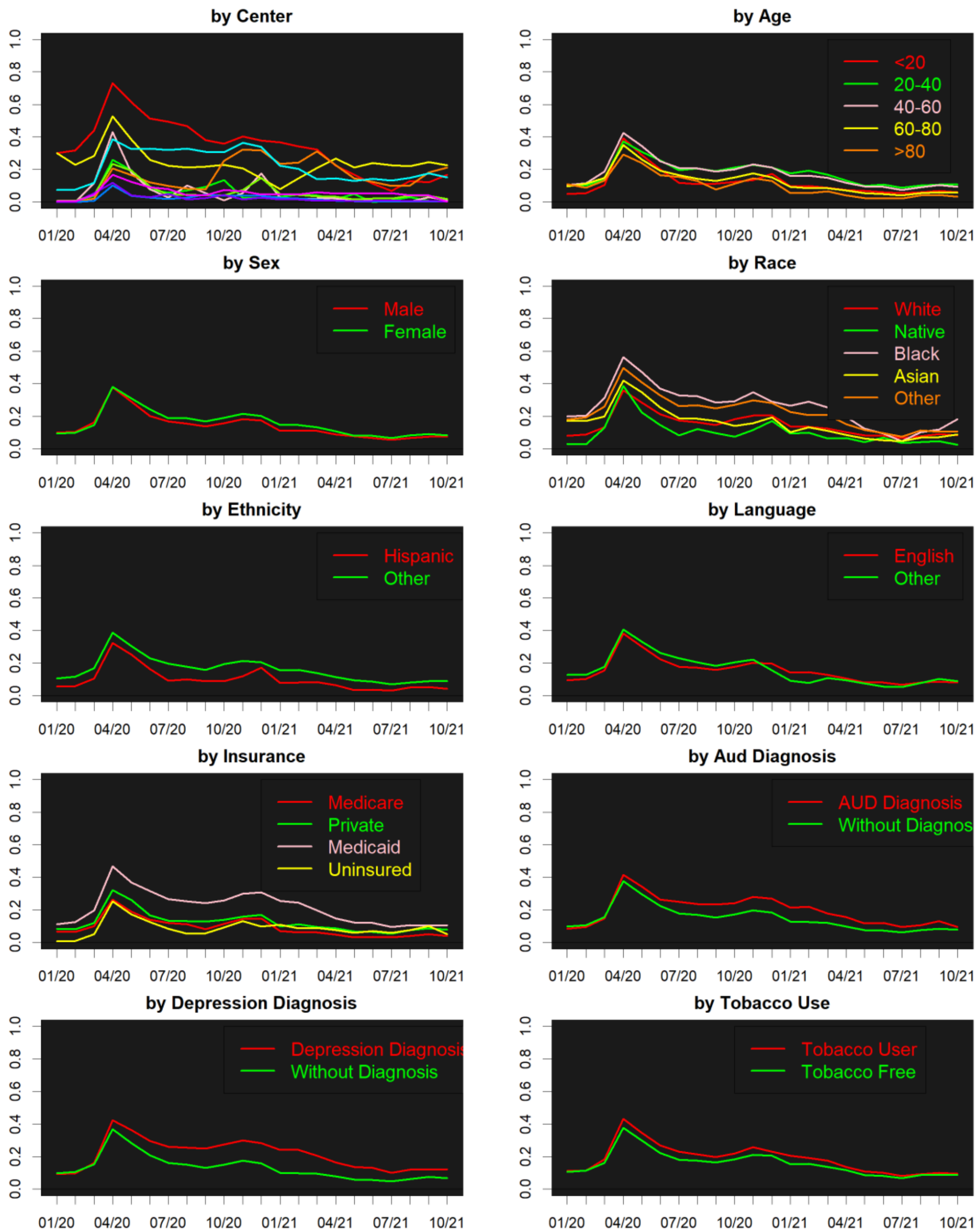
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