Inter-state variation in disability applications during the COVID-19 pandemic

Version: September 9, 2022

Pinka Chatterji*%, Yiran Han*, Kajal Lahiri*, Jinman Pang*, Cheng Yang$ & Yimeng Yin*#

The research reported herein was performed pursuant to grant RDR18000003 from the US Social Security Administration (SSA) funded as part of the Retirement and Disability Research Consortium. The opinions and conclusions expressed are solely those of the author(s) and do not represent the opinions or policy of SSA, any agency of the Federal Government, or NBER. Neither the United States Government nor any agency thereof, nor any of their employees, makes any warranty, express or implied, or assumes any legal liability or responsibility for the accuracy, completeness, or usefulness of the contents of this report. Reference herein to any specific commercial product, process or service by trade name, trademark, manufacturer, or otherwise does not necessarily constitute or imply endorsement, recommendation or favoring by the United States Government or any agency thereof.

Keywords: disability, Social Security, SSI, SSDI, COVID-19, pandemic

Affiliations: * The University at Albany; # Center for Retirement Research at Boston College; $Liaoning University; %NBER

ABSTRACT

We study inter-state differences in the monthly dynamics of disability applications during the Covid-19 pandemic. We use forecasting models to create counterfactual scenarios of disability applications, and then test whether state-level forecasting errors are associated with Covid-19 cases and state-level, pandemic-related policies. Data come from the SSA State Agency Monthly Workload Data from October 2000 to April 2022.

We contribute to existing literature in several ways. First, we address seasonal adjustment of the data during the pandemic and consider seasonal echoes and their potential consequences in our analysis. Second, our model incorporates spatial correlations across states. Third, we include a broad range of policy-related factors which may influence the effect of the pandemic on applications.

Our findings show a large, overall drop in disability applications during the Covid-19 pandemic. Based on seasonally adjusted data, we find that total applications were 84 percent of their 2017-2019 level in May 2020, and total applications were still 89 percent of their 2017-2019 level as of April 2022. The drop in disability applications is driven by falling SSI applications, which were still 77 percent of their 2017-2019 level as of April 2022.

Our analysis of state-level out-of-sample forecasting errors shows that during the pandemic, there has been considerable heterogeneity across states in the timing and magnitude of the pandemic's impact on disability applications. Forecasting errors generally are larger in magnitude for SSI and Concurrent applications relative to those of SSDI applications during the pandemic. We find that state unemployment rate, state of emergency declarations, and school closures are correlated with forecast errors for all types of applications. For SSI applications, ACA Medicaid expansion status is correlated with state-level forecast errors. These state-level factors appear to play a role in explaining intra-state variation in the effect of the pandemic on disability applications.

1. Introduction

The COVID-19 pandemic, and its associated health and economic burden, has unfolded and continues to progress quite differently across states in the U.S. These differences are due to a variety of factors including heterogeneity across states in population density, SES characteristics, health, fiscal realities, and policies (White & Hebert-Dufresne, 2020). Variation across states in the timing and magnitude of the pandemic, as well as variation in state-level policies, may have affected the dynamics of federal disability applications. In this paper, we seek to explain inter-state differences in the monthly dynamics of applications after the onset of the pandemic, and to understand how the effects of the pandemic on applications may have been mitigated by other factors including safety-net programs. Our primary methodological approach is to use a spatial forecasting model to create counterfactual predictions of applications, and then test whether state-level forecasting errors are associated with Covid-19 cases and state-level, pandemic-related policies. The analysis utilizes State Agency Monthly Workload Data (MOWL) merged with state-level information on COVID-19 cases and deaths and other state-level and national data of varying temporal frequency, including structural barriers, economic factors, and policies.

Our findings show a large, overall drop in disability applications during the Covid-19 pandemic. Based on seasonally adjusted data, we find that total applications were 84 percent of their 2017-2019 level in May 2020, and total applications were still 89 percent of their 2017-2019 level as of April 2022. The drop in disability applications is driven by falling SSI applications, which were still 77 percent of their 2017-2019 level as of April 2022. There was considerable heterogeneity across states in the timing and magnitude of the pandemic's impact on disability applications.

Our analysis of state-level out-of-sample forecasting errors shows that during the pandemic, there has been considerable heterogeneity across states in the timing and magnitude of the pandemic's impact on disability applications. Forecasting errors generally are larger in magnitude for SSI and Concurrent applications relative to those of SSDI applications during the pandemic. We find that state unemployment rate, state of emergency declarations, and school closures are correlated with forecast errors for all types of applications. For SSI applications, ACA Medicaid expansion status is correlated with state-level forecast errors. These state-level factors appear to play a role in explaining intra-state variation in the effect of the pandemic on disability applications.

2. Background

The Social Security Administration (SSA) administers SSDI (Social Security Disability Insurance) and SSI (Supplemental Security Income), the two largest safety-net programs supporting people with disabilities in the US. Both SSDI and SSI require that participants meet the SSA's definition of having a disability, which is restricted to: (1) disabilities that prevent individuals from having substantial gainful activity (SGA) (as of 2022, the SGA limit was earnings of $1,350 per month); (2) disabilities that preclude individuals from doing the kind of work done prior to the onset of disability or other work; and (3) disabilities that are expected to last at least a year or result in death (SSA, 2022a). The SSA periodically reviews beneficiaries' medical conditions to determine whether they are still disabling, with the frequency of these "Continuing Disability Reviews (CDRs)" depending on the nature of the disabling condition; see Lahiri et al. (1995) for further details.

SSDI is not means-tested and provides benefits to disabled workers who have recent earnings and work history, with the required earnings/work history depending on the age of the applicant. There were about 8.7 million SSDI beneficiaries as of 2020 (KFF, 2022). As of 2019, the average benefit was about $1,236 a month (CBPP, 2022). SSDI recipients become eligible for Medicare 29 months after the onset of disability. This lag is due to an initial 5-month waiting period to receive SSDI benefits after onset of disability, and then a required 24-month waiting period before becoming eligible for Medicare (KFF, 2022) during which the recipient is eligible for Medicaid.

While SSDI is designed for disabled people with some work history, SSI is means-tested, does not require any work history, and supports individuals who are disabled and/or elderly, and who have low income and assets. As of 2020, about 8 million people received SSI benefits, of whom 4.6 million were adults aged 18-64 years old, and the average monthly federal SSI payment was $576 (SSA 2022b). Most states supplement federal SSI benefits, and in 35 states and DC, SSI applicants automatically receive Medicaid as well if they are awarded SSI (SSA, 2022c). In the remaining states, obtaining Medicaid either requires a separate application with the same eligibility rules as those of SSI; or applying for Medicaid requires a separate application with different eligibility rules than those of SSI (SSA, 2022d).[1] SSI beneficiaries may be eligible for both SSI and SSDI at the same time; these concurrent beneficiaries are disabled people who meet both the work history requirements for SSDI and the income and assets requirements for SSI.

There is considerable variation across states in the percent of the population receiving disability benefits, with Alabama (AL), Arkansas (AR), Kentucky (KY), Maine (ME), Mississippi (MS), and West Virginia (WV) having the highest rates among nonelderly adults (7 percent or higher) (SSA, 2022e). Some of this state-level variation may result from demand-side factors affecting potential applicants' costs and benefits of applying for benefits, and/or demand-side factors affecting the likelihood of applicants being awarded benefits. These factors include differences across states in the prevalence and severity of disabling conditions, public policies that alter the incentives to apply for benefits, and, perhaps most importantly, labor market conditions (Lahiri et al. 2008, Gettens et al.,

[1] The states that require separate application but have the same eligibility rules are AK, ID, KS, NE, NV, OR, and UT. The states that require separate application and have different eligibility rules are CT, HI, IL, MN, MO, NH, ND, OK, VA.

2018; Coe et al., 2011). In fact, a large body of prior work shows that state economic conditions are linked to disability caseloads (examples include Autor & Duggan, 2003; Black et al., 2002; Duggan and Imberman, 2009; Maestas et al., 2021 and others; see Nichols et al. 2017 for a review).

Supply-side factors, such as geographic variation in the way benefits are administrated, also may play a role in explaining intra-state differences in disability caseloads. Kearney et al. (2021), for example, find that in geographic areas severely impacted by the Great Recession, longer appeal processing times are associated with slower growth in SSDI enrollment; in areas with relatively high baseline rates of SSDI participation, longer appeal processing time is additionally associated with a relative increase in employment growth (Kearney et al., 2021). Lahiri and Hu (2020) found that persistent differences in processing times, pending claims and organizational inefficiencies discourage disability applications differentially across states. Deshpande & Li (2019) find that closings of SSA field offices are associated with reductions in disability applications and recipients.

Some studies have focused on specific state-level policies that may affect the demand for disability benefits such as Medicaid expansions and minimum wages. Prior to recent Medicaid expansions which were targeted at low-income childless adults, most disabled people had no access to public health insurance programs other than through SSI and DI, particularly in states with low income-eligibility thresholds and states that lack of any kind of coverage for childless adults (Kennedy & Blodgett, 2014). If Medicaid expansions offered a new route to public insurance for disabled adults, then these expansions may be expected to reduce SSI and SSDI applications. On the other hand, Medicaid expansions may encourage some currently employed, privately insured workers to leave their jobs and apply for SSDI, since they now potentially could be covered by Medicaid during the waiting period required to obtain Medicare through SSDI.

Recent work suggests that Medicaid expansions have only mixed and small effects on SSI/SSDI-related outcomes. Schmidt et al. (2020), for example, drawing on data from contiguous counties, find that Affordable Care Act (ACA) Medicaid expansion status is not associated with county-level rates of SSI/SSDI applications and awards. Burns & Dague (2017), on the other hand, find that state Medicaid expansions targeted at childless adults which took place between 2001 and 2013 are associated with about a 7 percent decline in SSI participation. Chatterji & Li (2019) test whether early Affordable Care Act (ACA) Medicaid expansions in 2010 and 2011 in Connecticut (CT), Minnesota (MN), California (CA), and the District of Columbia (DC) affected applications, awards and the number of disability beneficiaries. In CT, the Medicaid expansion is associated a statistically significant, 7 percent reduction in SSI beneficiaries, but there is no evidence that the Medicaid expansions affected disability-related outcomes in MN, CA, or DC.

Similarly, there is little evidence that state-level minimum wages affect disability applications. Duggan & Goda (2020), using data from 2000-2015, find that changes in state-level minimum wages have only very small effects on disability applications. Englehardt (2020) using data from 2002-2017 finds no effects of state-level minimum wages on SSDI applications and awards. Existing research, therefore, does not support the idea that state-level differences in these two safety net policies (Medicaid eligibility and minimum wages) are important factors in explaining intra-state variation in disability caseloads.

The era of Covid-19 brings new urgency to understanding what factors triggered intra-state differences in disability caseloads and how state-level factors, particularly state-level policies, may affect disability applications. At the outset of the pandemic, disability applications were expected to surge, given the pandemic's disproportionate impact on disadvantaged groups and people with disabilities. As evidence for "long Covid" – persistent and sometimes disabling symptoms after recovery from Covid-19 - emerged, it seemed even more likely that there would upward pressure on disability applications (Hyde, 2022; Romig, 2022). Contrary to these expectations, however, the pandemic seems to have accelerated the steady decline in disability applications that has been occurring since about 2010 (Hyde, 2022). This acceleration may be related to the closure of in-person, walk-in services at SSA field offices between March 2020 and April 2022 (SSA, 2022f), and some predict a bounce-back in applications in coming years (Romig, 2022). At present, we know little about what factors are the driving forces behind disability applications during the pandemic, and how and why the pandemic-era dynamics and seasonality in applications may vary across states.

Existing, related literature on the COVID-19 pandemic largely has focused on the effects of state-level non-pharmaceutical interventions related to the pandemic on household behavior, labor market outcomes and the macro-economy (see, for instance, Goolsbee and Syverson 2020, Fernández-Villaverde and Jones 2020, Arnon et al. 2020). A recent study highlights cross-state heterogeneity in the impact of the pandemic on state Medicaid enrollment (Clemens et al., 2021). To our knowledge, no prior study has focused on documenting and explaining inter-state differences in the effect of the COVID-19 pandemic on the three types of disability applications.

Recent work by Goda et al. (2021, 2022 and forthcoming) is closely related to the present study. Goda et al. (2022a) estimate the effects of the pandemic on labor market outcomes among individuals aged 50-70 years old, as well effects of the pandemic on disability applications. Goda (2021), using data from January 2015 to March 2021, find that total applications for disability declined by about 15 percent during the pandemic, primarily driven by reductions in SSI applications (Goda et al., 2021). They also report decreases in Google search activity for the term “disability” during the pandemic period, which is consistent with the reduction in applications.

The authors suggest that pandemic-related demand-side factors, such as pandemic relief programs and the shift to telework, as well as pandemic-related supply-side factors, such as SSA office closures and stay-at-home orders, may explain the drop in disability applications. They find no evidence, however, that Internet connectivity, stay-at-home orders, and whether an area has a higher share of non-telework and non-essential jobs is associated with disability applications during the pandemic. In their most recent work, Goda et al. (2022) extend these analyses to include disability applications data up to and including March 2022. They find that disability applications remain depressed in the second year of the pandemic. They also find that expiration of pandemic UI programs is associated with small increases in disability applications, driven by increases in SSDI and Concurrent applications (Goda et al., 2022).

In this study, we build on Goda et al.'s work and, more broadly, contribute to the economics literature on disability caseloads by using a spatial forecasting model to: (1) quantify the effect of the pandemic on disability applications; and (2) explain how variation across states in the effects of the pandemic on applications may be attributed to various state-level and national factors. Since the incentives to apply are somewhat different between SSDI and SSI applicants, we examine the application dynamics for total applications as well as for SSDI, SSI and Concurrent applications separately. To identify relevant factors, we start with demographic, economic, and policy variables that have been identified by others (Despande & Li 2019, Rupp & Riley 2011; Guo & Burton 2012, Autor & Duggan, 2003) and then explore short-term, pandemic-specific factors, such COVID-19 cases and deaths, stay-at-home orders, UI applications, and broadband access.

3. Data

Our primary source of data is the SSA State Agency Monthly Workload Data (MOWL). MOWL is a publicly available seasonal data set which contains the monthly number of disability benefit applications, determinations, and allowances at state agencies, which process the vast majority of disability cases, and a federal agency and four extended service team sites that assist other states. MOWL records the number of claims for SSDI benefits only, SSI benefits only and the simultaneous filing by the same person for both SSDI and SSI benefits, which is referred to as “concurrent" filing. The sample period begins in October 2000 and data up to April 2022 are used in this paper. We use the number of initial claims (reflecting the first time the SSA reviews an application) per month at the state level. To obtain the number of claims at the national level, we sum claims from all component agencies (including state and federal agencies and extended service teams) in each month.

As discussed in more detail in the Methods section, we pre-treated the monthly disability application series for calendar effects and significant outliers. In the MOWL data, the SSA tabulates its caseload by “working month", which may have either 4 or 5 complete weeks depending on the number of Fridays falling in the corresponding calendar month. For this analysis, we need to make the number of applications comparable across months by excluding any variation due to varying length of months and calendar effects. This length-of-SSA-working-month effect can be removed by adjusting the number of weeks in each working month by 4.35, which is the “long-run” average number of weeks in a month. Outliers in the data are detected and adjusted using the procedure described in Hyndman (2021).

We obtain the not-seasonally-adjusted state-level monthly unemployment from the Local Area Unemployment Statistics (LAUS) provided by the Bureau of Labor Statistics (BLS). The LAUS state-level unemployment data are model-based estimates primarily based on inputs from the Current Population Survey (CPS), supplemented with information from Current Employment Statistics (CES). For the initial claims of unemployment insurance, the official data are weekly and we construct monthly initial claims series (not seasonally adjusted) using the same rule governing how SSA working months are formed, except that the dates of Saturdays (the last day of each reporting week of initial claims), instead of Fridays in the case of disability applications, are used to determine how weeks are grouped into SSA working months. The constructed monthly unemployment initial claims data are also adjusted for the length-of-SSA-working-month effect.

We also merge the MOWL with state-level information on COVID-19 cases, hospitalizations, and deaths, and wide variety of state-level, pandemic-related variables. These variables are listed, along with their construction and sources, in Appendix A.

4. Methods: Creating counterfactual scenarios of applications through a forecasting model

4.1 Conducting seasonal adjustment to MOWL data

Monthly disability applications exhibit a prominent seasonal pattern that features a winter trough followed by a spring peak and an August spike. The amplitude of the seasonal variations in disability applications range from -12% to 8% deviation from the long-term trend, and the overall seasonal variation accounts for about 80% of short-term fluctuations for all three types of disability applications. (Lahiri and Yin, 2022). In this study, we focus on the non-seasonal component of disability applications and conduct seasonal adjustment on the MOWL data using the U.S. census X13-ARIMA/SEATS program.

Large economic changes, such as the ones caused by the Great Recession and the COVID-19 pandemic, can pose great challenges for estimating seasonal components and conducting seasonal adjustment (Wright, 2013; Rinz, 2020; Lucca and Wright, 2021). One important challenge is that large economic changes during crises may distort the seasonally adjusted economic data in subsequent years if seasonal adjustment procedures mistakenly recognize a portion of the shocks as changes in seasonality, which is discussed by Wright (2013) and Lucca and Wright (2021) in the context of U.S. employment data and referred to as seasonal "echoes".[2] Lahiri and Yin (2022) found that conducting seasonal adjustment for the MOWL data using the X13 ARIMA/SEATS program under the default settings produces "seasonal echoes" in the seasonally adjusted data, and the pattern of the "seasonal echoes" in disability applications is similar to that in employment data found by Lucca and Wright (2021).

The distortions in seasonally adjusted data caused by the "seasonal echoes" can affect the analysis of disability applications during the COVID-19 pandemic. Obviously, the distortions will affect quantitative results obtained using seasonally adjusted data.[3] More importantly, the similarity between the seasonal echoes in disability applications and employment may cause spurious co-movement and potentially give rise to artificially strong correlation between disability application behavior and labor market conditions during the COVID-19 pandemic.

In order to produce seasonally adjusted disability application data free of "seasonal echoes", we conduct seasonal adjustment using a specification of the X13 ARIMA/SEATS program is similar to that discussed in Lucca and Wright (2021): the default outlier detection procedure is applied only up to Feb 2020, after which each month during the COVID-19 pandemic is manually treated as an

---

2 Wright (2013) found that in the initial releases of employment data after 2009, the seasonal adjustment filters assimilated part of the impact of the Great Recession into the seasonal component, resulting in seemingly strong employment data in springs of the subsequent years. The Federal Reserve Board made manual adjustments to mitigate the seasonal echo effects in the 2010 annual revision in the official industrial production statistics. Lucca and Wright (2021) found small but meaningful "seasonal echoes" in seasonally adjusted employment data after the outbreak of the COVID-19 pandemic.

3 For instance, with the automatic adjustment procedure the seasonally adjusted values of SSDI only applications from November to February in 2021 and 2022 are underestimated by about 2% in each month due to the seasonal echoes, and any analysis involving those periods, such as examining how disability applications are affected by certain policy measures, will be subject to the distortion.

additive outlier. The hardcoded outliers prevent the changes in the pandemic period distorting the seasonal components.

4.2 Forecasting disability applications using a spatial dynamic panel data model

We create a counterfactual scenario in which disability applications were not affected by the COVID-19 pandemic by forecasting state-level monthly disability applications based on data prior to the pandemic. Using data up to 2020:2 as the training dataset, we create a 12-month counterfactual scenario from 2020:3 to 2021:2 with the forecasted values which covers the outbreak of the COVID-19 pandemic and the implementation of many aggressive policy responses including the stay-at-home orders, enhanced UI programs, and stimulus checks. The differences between the actual and forecasted numbers of disability applications, or the forecast errors, reflect the impact of the pandemic on disability application behavior. We document the variation of the impacts across states and over time and examine the extent to which the variation is associated with the differences in the severity of the pandemic and policy responses across states. Below we describe the forecasting model employed to construct the counterfactual scenario.

4.2.1 Model specification

There are three major considerations in developing the model specification. First, we detect strong cross-sectional correlation in state-level disability application data and the forecasting model should accommodate and utilize this data feature. Spatial regression models can capture cross-sectional dependence between sets of contiguous or proximate geographic units (Elhorst 2012, 2014; Lee and Yu, 2010; Baltagi et al. 2019; Goulard et. al, 2017). Giacomini (2004) argue that ignoring spatial correlation even when it is weak leads to highly inaccurate forecasts. The most general form of spatial models includes time lag, spatial lag, and space-time lag of both dependent and independent variables and allows for spatial dependence in the error term. In practice, a subset of these model features is sufficient to capture the spatial dependence. [4]

Second, we consider models with coefficients that vary across states to allow for heterogeneity. Typical panel data models impose homogeneity restriction on model parameters across units. The pooling restriction can usually yield superior out-of-sample forecast performance even it is rejected by a poolability test, mainly because the parsimonious specification can significantly reduce the variance of the estimates in the bias-variance trade-off. (Maddala et al., 1997, Baltagi et al., 2000, Driver et al. 2004). However, Hoogstrate et al. (2000) investigated the large T with fixed N asymptotics of the pooled models and showed that forecasts based on pooled models will be outperformed by unpooled forecasts as long as the time dimension gets large enough. The MOWL data is a long panel with T = 259 and N = 51, therefore it is important to examine whether relaxing the homogeneity restriction can improve forecast accuracy.

Third, we consider economic and labor market variables as leading indicators in the forecast of disability applications. The association between disability applications and unemployment has been well documented (Autor and Duggan, 2003; Duggan and Imberman, 2009; Maestas et al. 2021). Mechanisms through which unemployment can affect disability applications include (1) the onset of unemployment may trigger working individuals with disability to apply for disability benefit; (2) high unemployment rate indicates dim prospect of reemployment for displaced workers with disability when making the decision on whether to apply for disability benefits or keep seeking new

[4] Elhorst (2012) shows that the most general specification of SDPD is not identifiable.

jobs.[5] Leading indicators we test in the forecasting model include the number of unemployment, unemployment rate, UI initial claims, and Coincident Index.

The model selection is based on the out-of-sample forecast performance from an expanding-window forecast experiment with the training dataset starting from 2015:1.[6] The model selected to forecast disability applications is a spatial dynamic panel data (SDPD) model with heterogenous coefficients for the lagged dependent variable and Coincident Index and UI initial claims as leading indicators.

For each type of disability application, denote the number of applications for state i and month t as $Y_{i,t}$ (subscript for disability application is omitted for simplicity). For an h-step ahead forecast, data are first transformed into h-month growth rates by taking h-th order log difference:

$$y_{i,t}^{(h)} = y_{i,t} - y_{i,t-h}$$

where $y_{i,t} = log\ Y_{i,t}$. The following model is estimated:

$$\mathbf{y}_t^{(h)} = \rho \mathbf{W} \mathbf{y}_t^{(h)} + \boldsymbol{\theta}' \mathbf{y}_{t-h}^{(h)} + \mathbf{X}_{t-h}^{(h)} \boldsymbol{\beta} + \boldsymbol{\varepsilon}_t$$

where $\boldsymbol{\theta}$ is a 51×1 vector that contains heterogenous coefficients for each state plus DC. The time lag of the dependent variable $\mathbf{y}_{t-h}^{(h)}$ capture the regular autocorrelation, and the spatial lag term $\mathbf{W}\mathbf{y}_t^{(h)}$ captures the contemporaneous spatial correlation with neighboring states. $\mathbf{W}$ is a spatial weight matrix that describes the structure of interdependence across states and in this paper it is constructed

[5] This point is well illustrated in the dynamic programming model described in Autor and Duggan (2003), where a high probability of job loss and low probability of reemployment would raise the value of applying for benefits immediately after unemployment and lower the value of remaining in job market.
[6] Starting from an initial date, models are estimated using information available in current and past periods, and forecasts are made at forecast horizons of from 1 to 12 months. Then we move forward by 1 month, expanding the information set, re-estimating the models, and making forecasts.

based on the k-nearest-neighbor criterion with k = 5: the element $w_{i,j}$ is equal to the inverse distance between the central points of state i and state j if state j is one of the 5 nearest neighbors of state i, and 0 otherwise. The rows of W are standardized to have sum 1. Also used W created based on contiguity, differences are small. $\mathbf{X}_{t-h}^{(h)}$ includes h-month change of the two leading indicators: coincidence Index and monthly UI initial claims. The model is estimated by the QMLE method described in Yu et al. (2008).

4.2.2 Forecasting disability applications and constructing counterfactual scenario

For each type of disability application, the h-step forecasts conditional on information at t are given by

$$\hat{\mathbf{y}}_{t+h|t}^{(h)} = (\mathbf{I} - \hat{\rho}\mathbf{W})^{-1}\left(\hat{\boldsymbol{\theta}}'\mathbf{y}_t^{(h)} + \mathbf{X}_t^{(h)}\hat{\boldsymbol{\beta}}\right)$$

With the forecasted h-month ahead change rate, h-month ahead forecast of the number of disability application and the forecast error can be calculated as

$$\hat{\mathbf{Y}}_{t+h|t} = \exp\left(\mathbf{y}_t + \hat{\mathbf{y}}_{t+h|t}^{(h)}\right)$$

$$\mathbf{e}_{t+h}^{(h)} = \mathbf{Y}_{t+h} - \hat{\mathbf{Y}}_{t+h|t}$$

To construct the counterfactual scenario of disability application for the period from 2020:3 to 2021:2, we estimate the model with $h = 1, 2, 3, \ldots, 12$ using data from 2000:10 to 2020:2 for each type of disability application and produce 1- to 12-step ahead forecasts for each state. The counterfactual value for 2020:3 is given by the 1-step forecast, the counterfactual value for 2020:4 is given by the 2-step forecast, and the counterfactual values for later months up to 2021:2 are given by the corresponding forecasts in the same manner.

5. Results

5.1 Descriptive statistics

Figures 1a-d presents total monthly disability applications, as well as for the three sub-categories (SSDI, SSI and Concurrent), for the U.S. over the time period January 2017 to April 2022. The figures are based on pre-treated, seasonally adjusted data, as discussed above.[7] Each figure shows the national trend in applications of that type, as well as trends for the eight states with the highest number of applications of that type during the entire MOWL time period, October 2000 – April 2022.[8] In Appendix B, we show a similar set of figures for each SSA region, showing trends in applications for the whole SSA region, as well as trends for each state that makes up the region; in these figures, the normalization for the regional (state) figures is based on the average number of applications in the region (state) between 2017-2019. The dotted vertical line in each figure corresponds to March 2020.

. Figure 1a shows total applications, while Figures 1b, 1c and 1d show SSDI, SSI and Concurrent applications respectively. In Figure 1a, we observe a sharp drop in total applications at the start of the pandemic. In May 2020, total applications had declined to 84 percent of their typical level during 2017-2019 time period. Total applications stagnated for more than a year, remaining about 85-94% of their typical level until the last quarter of 2021, when applications started to return closer to previous levels. As of April 2021, however, total applications were still 89 percent of their typical level during the 2017-2019 time period.

[7] The data shown in the figures are normalized by the average number of monthly applications between 2017 and 2019. Specifically, each number in the figures is equal to 100 * (actual number of applications in the month / (mean (monthly applications from 2017 to 2019)).
[8] The eight states are selected by first ranking states by the number of applications in each month-year, and then selecting the eight states that are ranked as one of the highest eight the most times between October 2020 and April 2022.

Figure 1a shows that there was considerable heterogeneity, as well as volatility, in the top eight states' experiences during the pandemic. For example, North Carolina started to return to its typical level of applications at the end of 2020, but then applications fell again in early 2021 and much lower than previous levels for the remaining time period (in April 2022, total applications were still only 82 percent of their level in 2017-2019). Texas, on the other hand, appeared less affected at the start of the pandemic but then experienced extreme volatility in applications starting in mid-2021.

Figures 1b-d shows these data by application type. For all types of applications (SSDI, SSI and Concurrent), there was a striking increase in volatility in the number of applications during the pandemic (March 2020 – April 2022) relative to 2017-2019. The sudden drop in applications at the start of the pandemic, however, and the continued, persistent stagnation in the number of applications, is driven by SSI and concurrent applications. As of April 2022, SSI and concurrent applications were 77 and 82 percent of their typical levels in 2017-2019 respectively, while SSDI applications were 103 percent of their typical level in 2017-2019.

In Appendix B, we show these figures by SSA region: Atlanta, Boston, Chicago, Dallas, Denver, Kansas City, New York, Philadelphia, San Francisco, and Seattle. Each figure also shows trends in the individual states that make up the region. There was considerable heterogeneity across SSA regions in the timing and magnitude of the pandemic's impact on disability applications, and also heterogeneity within states in each region.

5.2 DD models and event studies: Effects of state-level factors on applications during the pandemic

Most prior research has used event study and difference-in-difference (DD) models to estimate the effects of pandemic-related variables on labor market and related outcomes. Before moving to the forecasting results, we follow methods used by prior researchers in this area to study effects of pandemic-related variables on disability applications. Details about the methods used and the findings are presented in Appendix C. Here, we focus on summarizing the findings descriptively.

<u>Covid cases and deaths, Medicaid, and pandemic-related policies</u>

During the first year of the pandemic (approximately March 2020 – February 2021), the most important state-level variables potentially affecting disability applications may have been factors restricting potential applicants' ability to leave home, and factors related to being able to apply for benefits online, since SSA offices were closed for in-person visits. These factors are likely to include the prevalence and severity of the disease itself (which we measure by state, monthly, cumulative number of cases and deaths), as well as policies that restricted movement (e.g., stay-at-home orders, school closings), and broadband access.

In addition to these variables, we consider whether the state had expanded Medicaid under the Affordable Care Act, and whether a potential applicant lived in a state in which a person would automatically become eligible for Medicaid if SSI were awarded. In states that expanded Medicaid, there may be less incentive to overcome pandemic-related obstacles and apply for disability benefits since public health insurance is more readily available. In states where SSI and Medicaid eligibility are linked, there may be more incentive to apply during the pandemic, since a successful SSI application would also offer health insurance coverage.

From the DD results in Appendix C (Tables 1-3), we observe the following patterns. First, we find larger and more consistent negative effects of the pandemic on SSI and concurrent applications vs. SSDI applications. Second, the state unemployment rate is negatively correlated with SSI and concurrent applications during the pandemic, which possibly suggests that the unemployment rate is picking up the degree of shutdown in the state, which is preventing vulnerable individuals from applying for benefits. Similarly, school closings are associated with reductions in SSI and concurrent applications but not with SSDI applications. Finally, we find that Medicaid expansion is associated with a larger drop in SSDI applications during the pandemic, but not SSI or concurrent applications. This finding may suggest that potential SSDI applicants who were motivated by the possibility of gaining public health insurance could delay or forgo applying for disability benefits during the pandemic since they had greater access to Medicaid. However, we acknowledge that there are other explanations as well, since states that expanded Medicaid share other characteristics that may affect the relationship between the pandemic and disability applications. We do not find statistically significant interactions between broadband access and the pandemic period, and there is no consistent evidence that Covid-19 cases and deaths are associated with the effects of the pandemic on disability applications.

Termination of pandemic UI programs

The CARES Act included Federal Pandemic Unemployment Compensation (FPUC), a weekly additional payment of $600 per week to calculated state UI benefits between April 5, 2020, and July 26, 2020. The $600 additional UI benefits were extended to September 6, 2021 at a reduced amount of $300 (BEA, 2021). Twenty-five states chose to end their participation in FPUC (with twenty-one of these states also ending participation in PEUC and PUA) in June and July of 2021 out of concern that generous benefits were dampening workers' efforts to find jobs and return to work (Dube, 2021a).

We test whether early termination of pandemic UI in June 2021 is associated with disability applications, limiting the sample to DC and states that ended pandemic UI in either June or September 2021 (this sample restriction excludes AZ, IN, LA, and TN). We also test whether the September 2021 termination is associated with disability applications. These findings are shown in Appendix C. Early termination of pandemic UI programs in June 2021 is not associated with changes in disability applications. There is a slight increase in disability applications in August 2021 in states that terminated in June vs. states that terminated in September, but this effect is not statistically different from zero. The September termination, however, is associated with statistically significant increases in SSDI and concurrent applications in the fourth quarter of 2021.

5.3 Spatial model findings

Figure 2 shows one-year-ahead, state-level forecast errors from out-of-sample forecasts of each state's monthly number of applications for the time period January 2016 to April 2022. The figure shows nine states with the largest numbers of applications (CA, FL, NY, PA, OH, MI, NC, MA, WA).[9] Prior to the pandemic (January 2016 – February 2020), the model performs well, and forecasting accuracy is high for all states shown. There is little heterogeneity across states prior to the pandemic; one exception is the SSDI and Concurrent applications in Texas, which are over-estimated by the model in the second half of 2019.

There is a striking change in forecast accuracy during the pandemic period (March 2020 – April 2022). First, forecasting accuracy deteriorates substantially for all application categories, but particularly for SSI and Concurrent applications (Figure 2). Second, the deterioration is persistent, with some states showing forecast errors that are much larger compared to those of the pre-pandemic period even in the middle of 2021, more than a year into the pandemic. Third, applications are extremely volatile during the pandemic, with forecasting error swinging up and down for some states across months. Finally, there is substantial heterogeneity across the states shown in Figure 2. In Massachusetts, for example, SSI and Concurrent applications are over-estimated in the first year of the pandemic, but then forecast accuracy improves later during the pandemic period. In Florida, the

[9] For clarity in the figure, we omit TX and IL because these states have much larger fluctuations than the other states.

forecasting errors generally are large and negative in the first year of the pandemic, but they start to become positive in sign in the second year of the pandemic.

Figures 3-6 show data that allows a closer look at the variation across states in forecast errors. These figures show statistics for all applications (Figure 3), SSDI applications (Figure 4), SSI applications (Figure 5) and concurrent applications (Figure 6). The time period shown is the first year of the pandemic, March 200 – February 2021. Each figure shows total percentage forecast error for all states and DC for March 2020 – February 2021 based on 12-month-ahead forecasts.

Starting with Figure 1, which shows total applications, the statistics show that in all but seven states (DE, TX, GA, ND, NM, UT, KS) and DC, forecast errors were negative for this time period. Nevertheless, the size of the forecast error varied widely even within states with negative forecast errors, ranging from -67 percent in Alaska to -1 percent in New Hampshire.

Patterns across states were quite different for SSDI applications vs. SSI and concurrent applications. For SSDI applications, 16 states and DC had positive forecast errors (e.g., there were more applications that the model predicts). The magnitudes of the negative SSDI forecast errors in the remaining states ranged from -.2 percent in Mississippi to -49 percent in Alaska (Figure 4). For SSI applications, only 4 states had positive forecast errors, and the magnitudes of the negative SSI forecast errors in the remaining states ranged from -3 percent in Delaware to -73 percent in Alaska (Figure 5). For concurrent applications, 6 states had positive forecast errors, and the magnitudes of the negative SSI forecast errors in the remaining states ranged from -2 percent in Wyoming to -88 percent in Alaska (Figure 6).

There are some states for which forecast errors are similar in direction and magnitude across application types. For Alaska and DC, for example, errors are large in magnitude for SSDI, SSI, and concurrent (although forecasting error is negative for Alaska and positive in DC). Other states have quite different forecasting patterns across application type. Georgia, for example, has a forecast error of 15 percent for SSDI applications but the errors for SSI and concurrent are – 5 percent and 4 percent, respectively.

State-level factors, including the magnitudes of Covid-19 cases/deaths and state-level policies, may explain some this intra-state variation in forecast errors. In Table 1, we show results from regressions in which the dependent variable is the monthly state-level forecast error, and, on the right-hand side of the model, we include monthly pandemic-related policy variables, monthly cumulative cases and deaths from Covid-19, and state fixed effects. The time period considered is March 2020 – February 2021, the first year of the pandemic. We also consider a set of models that include time-invariant (during the first year of the pandemic) state characteristics (Medicaid policies, Internet connectivity) which do not include state fixed effects.

The findings suggest that the unemployment rate, state-of-emergency declarations, and school closures are correlated with state-level forecasting errors. The cumulative death rate is negatively associated with forecast error for SSDI and concurrent applications, suggesting that higher burden of disease may affect individuals' ability to apply. The ACA Medicaid expansion is also negatively associated with forecast error for SSI applications. This may be because individuals in expansion states were better able to obtain Medicaid without applying for disability compared to those in non-expansion states.

6. Conclusions

Understanding how the pandemic has affected state-level disability applications since March 2020 is critical for policymakers to grapple with the fiscal impact of COVID-19, as well as to anticipate demands on the SSA front-line staff who process applications. In addition, it may shed light on long-term effects on disability applications in the aftermath of COVID-19. In future research, we plan to examine the effects of state-level factors on forecasting errors in the second year of the pandemic.

References

Arnon, Alexander, John Ricco, and Kent Smetters (2020). Epidemiological and Economic Effects of Lockdown, Working Paper, Penn Wharton Budget Model 2020.

Autor, David and Mark Duggan (2003). The rise in the disability rolls and the decline in unemployment. *Quarterly Journal of Economics* 118 (1), 157-205.

Baltagi, Badi H., James M. Griffin, and W. Xiong. "To Pool or Not to Pool: Homogeneous versus Heterogeneous Estimators Applied to Cigarette Demand." Review of Economics and Statistics 82 (2000): 117–26.

Baltagi, Badi, Bernard Fingleton and Alain Pirotte (2014). Estimating and forecasting with a dynamic spatial panel data model, *Oxford Bulletin of Economics and Statistics,* 76 (1). 111-138.

Baltagi, Badi, Bernard Fingleton, and Alain Pirotte (2019). A time-space dynamic panel data model with spatial moving average errors, *Regional Science and Urban Economics*, 76, 13-31.

Bitler, Marianne & Hilary Hoynes (2020). The social safety net in the wake of COVID-19. NBER Working paper 27796.

Black, Dan, Kermit Daniel, and Seth Sanders. 2002. "The Impact of Economic Conditions on Participation in Disability Programs : Evidence from the Coal Boom and Bust." The American Economic Review 92 (1): 27–50.

Burns, Marguerite & Dague, Laura. (2017). The effect of expanding Medicaid eligibility on Supplemental Security Income program participation. Journal of Public Economics 149: 20-34.

Bureau of Economic Analysis (BEA), "How will the expansion of unemployment benefits in response to the COVID-19 pandemic be recorded in the NIPAS?" Available at: https://www.bea.gov/help/faq/1415, Accessed 9/10/21.

Center on Budget and Policy Priorities (CBPP), "Chartbook: Social Security Disability Insurance," Available at: https://www.cbpp.org/research/social-security/social-security-disability-insurance-0#:~:text=SSDI%20benefits%20are%20modest.,less%20than%20%242%2C000%20a%20month. Accessed 8/2022.

Chatterji, Pinka & Li, Yue. (2017). Early coverage expansions under the Affordable Care Act and Supplemental Security Income participation. *The Journal of the Economics of Ageing* 10: 75- 83.

Clemens, Jeffrey, Ippolito, Benedic N. & Veuger, Stan. Medicaid and Fiscal Federalism during the COVID-19 pandemic. NBER working paper 28670.

Coe, Norma B., Haverstick, Kelly, Munnell, Alicia H. & Webb, Anthony. (2011). What explains state variation in SSDI application rates? Center for Retirement Research at Boston College Working Paper 2011-23.

Deshpande, Manasi & Yue Li (2019). Who is screened out? Application cost and the targeting of disability programs, *American Economic Journal: Economic Policy*, 11 (4), 213-248.

Driver, C., K. Imai, P. Temple, and A. Urga. "The Effect of Uncertainty on UK Investment Authorisation: Homogeneous vs. Heterogeneous Estimators." Empirical Economics 29 (2004): 115–28.

Dube, Arindrajit. (August 20, 2021). "Early withdrawal of pandemic UI: impact on job finding in July using Current Population Survey." Available at: https://arindube.com/blog-posts/. Accessed 9/9/21.

Duggan, Mark and David, Autor (2003). The growth in the Social Security disability rolls: A fiscal crisis unfolding, *Journal of Economic Perspectives*, 20 (3). 71-96.

Duggan, Mark G., and Scott A. Imberman. 2009. "Why Are the Disability Rolls Skyrocketing? The Contribution of Population Characteristics , Economic Conditions , and Program Generosity." In Health at Older Ages: The Causes and Consequences of Declining Disability among the Elderly, 337–79. January. University of Chicago Press.

Duggan, Mark G. & Goda, Gopi Shah. 2020. "The Minimum Wage and Social Security Disability Insurance." NBER Center paper NB20-17.

Elhorst, J. Paul (2012). Dynamic spatial panels: models, methods, and inferences. *Journal of Geographical Systems*, 14, 5-28.

Elhorst, J. Paul (2014). *Spatial Econometrics: from Cross-Sectional Data to Spatial Panels*. Springer, Heidelberg.

Engelhardt, Gary V. 2020. "The minimum wage and DI claims." Economics Letters 194: 109355.

Fernández-Villaverde, Jesús & Charles Jones (2020). Macroeconomic outcomes and COVID-19: A progress report. NBER Working paper 28004.

Giacomini, Raffaella, and Clive W.J. Granger. "Aggregation of Space-Time Processes." Journal of Econometrics 118 (2004): 7–26.

Goulard, Michael, Thibault Laurent, and Christine M Thomas-Agnan (2017). About predictions in spatial SAR models: optimal and almost optimal strategies. *Spatial Economic Analysis* 12 (2-3), 304-325.

Gettens, John, Lei, Pei-Pei, & Henry, Alexis D. (2018). Accounting for geographic variation in social security disability program participation. *Social Security Bulletin* 78, 29-47.

Goolsbee, Austan & Chad Syverson (2020). Fear, lock down, diversion: Comparing drivers of pandemic economic decline 2020, Working paper 2743. National Bureau of Economic Research.

Goda, Gopi Shah, Emilie Jackson, Lauren Hersch Nicholas, and Sarah See Stith. 2021. "The Impact of Covid-19 on Older Workers' Employment and Social Security Spillovers." w29083. Cambridge, MA: National Bureau of Economic Research. https://doi.org/10.3386/w29083.

Goda, Gopi Shah, Emilie Jackson, Lauren Hersch Nicholas, and Sarah See Stith. The impact of Covid-19 on older workers' employment and Social Security spillovers. Forthcoming in Journal of Population Economics.

Goda, Gopi Shah, Emilie Jackson, Lauren Hersch Nicholas, and Sarah See Stith. (2022). "The Impact of Covid-19 on Older Workers' Employment and Social Security Spillovers: Evidence from Year 2."RDC conference presentation, July 2022.
Hyndman, Rob J. 2021. "Detecting Time Series Outliers." 2021. https://robjhyndman.com/hyndsight/tsoutliers/.

Guo, Steve & John Burton Jr. (2012). The growth in applications for social security disability insurance: A spillover effect from workers' compensation. *Social Security Bulletin*, 72 (3), 69-88.

Hale, Thomas et al. (2020). Oxford COVID-19 Government Response Tracker. Blavatnik School Government.

Hyde, J.S. (2022). The Pandemic Offers a Road Map to Reimagine the Federal Disability Application Process. Available at: https://www.mathematica.org/blogs/the-pandemic-offers-a-road-map-to-reimagine-the-federal-disability-application-process.

Hoogstrate, André J., Franz C. Palm, and Gerard A. Pfann. "Pooling in Dynamic Panel-Data Models: An Application to Forecasting GDP Growth Rates." Journal of Business & Economic Statistics 18, no. 3 (2000): 274–83.

Kaiser Family Foundation (2022). "State Health Facts." Available at: https://www.kff.org/medicare/state-indicator/total-disabled-social-security-disability-insurance-ssdi-beneficiaries-ages-18-64/?currentTimeframe=0&sortModel=%7B%22colId%22:%22Location%22,%22sort%22:%22asc%22%7D. Accessed 8/22.

Kearney, Melissa, Price, Brendan M. & Wilson, Riley. (2021). Disability insurance in the great recession: Ease of access, program enrollment, and local hysteresis. NBER Working Paper 28725.

Kennedy, J. & Blodgett, E. (September 20, 2012). Health insurance-motivated disability enrollment and the ACA. New England Journal of Medicine, 367:e16.

Lahiri, Kajal and Jianting Hu. (2020). Productive Efficiency in Processing Social Security Disability Claims: A Look Back at the 1989- 95 Surge, *Empirical Economics*, Special issue Honoring Badi Baltagi. Vol 60 (1), January 2021, 419-457.

Lahiri, Kajal, Danny. R. Vaughan and Bernard Wixon. (1995). "Modeling SSA's Sequential Disability Determination Process Using Matched SIPP Data", *Social Security Bulletin*, Vol. 58, Winter 1995, pp. 3-42.

Lahiri, Kajal, Jae Song and Bernard Wixon. (2008). "A Model of Social Security Disability Insurance Using Matched SIPP/Administrative Data", *Journal of Econometrics*, 145, 2008, 4-20.

Lahiri, Kajal & Yin, Yimeng. (2020). Seasonality in U.S. Disability Applications, SUNY Albany.

Lee, Lung-fei, and Jihai Yu. "Estimation of Spatial Autoregressive Panel Data Models with Fixed Effects." Journal of Econometrics 154, no. 2 (February 1, 2010): 165–85.

Lucca, David, and Jonathan H. Wright. 2021. "Reasonable Seasonals? Seasonal Echoes in Economic Data after COVID-19." *Federal Reserve Bank of New York Liberty Street Economics* (blog). March 25, 2021. https://libertystreeteconomics.newyorkfed.org/2021/03/reasonable-seasonals-seasonal-echoes-in-economic-data-after-covid-19/.

Maddala, G.S., R.P. Trost, H. Li, and F. Joutz. "Estimation of Short-Run and Long-Run Elasticities of Energy Demand from Panel Data Using Shrinkage Estimators." Journal of Business and Economic Statistics 15 (1997): 90–100.

Maestas, Nicole, Mullen, Kathleen J. & Strand, Alexander. (2014). Disability insurance and health insurance reform: Evidence from Massachusetts. *American Economic Review: Papers and Proceedings* 104, 329-335.

Maestas, Nicole, Kathleen J. Mullen, and Alexander Strand. "The Effect of Economic Conditions on the Disability Insurance Program: Evidence from the Great Recession." Journal of Public Economics 199 (July 1, 2021): 104410. https://doi.org/10.1016/j.jpubeco.2021.104410.

Mueller, Andreas I, Jesse Rothstein, and Till M von Wachter. 2013. "Unemployment Insurance and Disability Insurance in the Great Recession." NBER Working Paper No. 19672, November. http://www.nber.org/papers/w19672.

Nichols, A., Schmidt, L. & Sevak, P. (2017). Economic Conditions and Supplemental Security Income Application. *Social Security Bulletin*, Vol. 77 No. 4.

Rinz, Kevin. 2020. "Understanding Unemployment Insurance Claims and Other Labor Market Data During the COVID-19 Pandemic." https://kevinrinz.github.io/covid19_labordata.pdf.

Romig, K. (2022). SSA Needs Large Funding Boosts Following Pandemic, Years of Underinvestment. https://www.cbpp.org/blog/ssa-needs-large-funding-boosts-following-pandemic-years-of-underinvestment

Rupp, Kalman and Riley, Gerald F. (2011). Longitudinal Patterns of Participation in the Social Security DisabilityInsurance and Supplemental Security Income Programs for People with Disabilities (May). *Social Security Bulletin*, 71 (2), 25-51.

Schmidt, Lucie, Shore-Sheppard, Laura D. & Watson, Tara. (2020). The impact of the ACA Medicaid expansion on disability program applications. *American Journal of Health Economics* 6, 444-476.

Social Security Administration (2022a), "How you qualify" Available at: https://www.ssa.gov/benefits/disability/qualify.html#anchor2, Accessed 8/2022.

Social Security Administration (2022b), "Fast Facts & Figures about Social Security, 2021." Available at: https://www.ssa.gov/policy/docs/chartbooks/fast_facts/2021/fast_facts21.html#page24. Accessed 8/2022.

Social Security Administration (2022c), "Understanding Supplemental Security Income SSI Benefits -- 2022 Edition" Available at: https://www.ssa.gov/ssi/text-benefits-ussi.htm. Accessed 8/2022.

Social Security Administration (2022d), "What is Medicaid?" Available at: https://www.ssa.gov/disabilityresearch/wi/medicaid.htm

Social Security Administration (2022e), Annual Statistical Report on the Social Security Disability Insurance Program, 2016. https://www.ssa.gov/policy/docs/statcomps/di_asr/2016/sect01.html

Social Security Administration (2022f), Social Security Administration to Resume In-Person Services at Local Social Security Offices, https://blog.ssa.gov/social-security-administration-to-resume-in-person-services-at-local-social-security-offices/#:~:text=I%20am%20pleased%20to%20announce,%2C%20on%20April%207%2C%202022.

White, E.R. & Hebert-Dufresne, L. (2020). State-level variation of initial COVID-19 dynamics in the United States. PLoS ONE 15(10): e0240648. https://doi.org/10.1371/journal.pone.0240648.

Wright, Jonathan H. 2013. "Unseasonal Seasonals." Brookings Papers on Economic Activity. https://www.brookings.edu/wp-content/uploads/2016/07/2013b_wright_unseasonal_seasonals.pdf.

Yu, Jihai, Robert de Jong, and Lung-fei Lee. "Quasi-Maximum Likelihood Estimators for Spatial Dynamic Panel Data with Fixed Effects When Both n and T Are Large." Journal of Econometrics 146, no. 1 (September 1, 2008): 118–34.

Table 1: Regressions of state forecast errors on pandemic-related variables

	SSDI				SSI				Concurrent			
Stay at home	-7.517	-212.320	-209.328	-188.649	32.780	-104.511	-119.533	-115.078	47.376	-42.396	-44.810	-31.516
	(79.056)	(300.411)	(291.575)	(296.294)	(61.232)	(148.168)	(147.240)	(152.998)	(39.582)	(140.774)	(136.344)	(139.476)
Emergency	2.216	344.361***	396.986***	288.841**	16.345	134.668***	193.356***	176.516***	-3.424	245.103**	281.178***	226.744**
	(105.948)	(126.195)	(112.273)	(126.840)	(67.551)	(46.418)	(56.710)	(49.829)	(42.423)	(94.500)	(88.967)	(94.077)
School closure	49.746	-187.964**	-229.664**	-226.934**	-36.024	-42.366	-32.249	-7.347	-13.960	-103.474***	-118.288***	-113.981***
	(60.689)	(81.567)	(97.905)	(91.334)	(52.723)	(32.129)	(30.677)	(36.021)	(34.122)	(36.684)	(44.074)	(41.150)
Restaurant closure	111.413	341.432	337.173	323.999	-1.918	83.515	91.781	89.787	58.601	179.404	179.651	171.108
	(74.462)	(245.445)	(238.182)	(242.399)	(48.545)	(125.143)	(124.188)	(128.208)	(41.991)	(119.568)	(116.131)	(118.821)
Umeploy_rate	-1188.710	-3013.980***	-2704.980**	-2971.128***	221.031	-522.649	-625.601	-734.362*	-340.127	-1510.915***	-1407.948**	-1537.588***
	(723.818)	(1046.484)	(1034.926)	(878.742)	(536.013)	(415.708)	(479.568)	(381.689)	(428.403)	(527.242)	(539.436)	(443.529)
Cum_death	-0.020*				0.010				-0.011*			
	(0.011)				(0.008)				(0.007)			
Cum_case	0.000				-0.000				0.000			
	(0.000)				(0.000)				(0.000)			
Medicaid_ACA		0.088				-119.816*				-29.106		
		(76.482)				(66.972)				(45.322)		
High_connect			-113.411				-44.702				-57.855	
			(87.537)				(59.712)				(49.030)	
Group1				254.365***				66.834				161.915***
				(66.567)				(57.276)				(44.583)
Group2				103.408				-74.875				23.070
				(97.297)				(83.691)				(59.487)
Constant	-19.244	-224.231	-203.516	-188.095	-45.872	-9.038	-131.950**	-149.434***	-15.020	-181.819	-203.133*	-198.599*
	(105.166)	(187.419)	(174.819)	(161.645)	(69.237)	(88.052)	(52.891)	(52.221)	(42.158)	(115.903)	(106.980)	(101.418)
Observations	612	612	612	612	612	612	612	612	612	612	612	612
Adjusted R^2	0.600	0.088	0.102	0.124	0.328	0.034	0.014	0.022	0.526	0.077	0.085	0.115
Year Fixed Effect	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
State Fixed Effect	Y	N	N	N	Y	N	N	N	Y	N	N	N

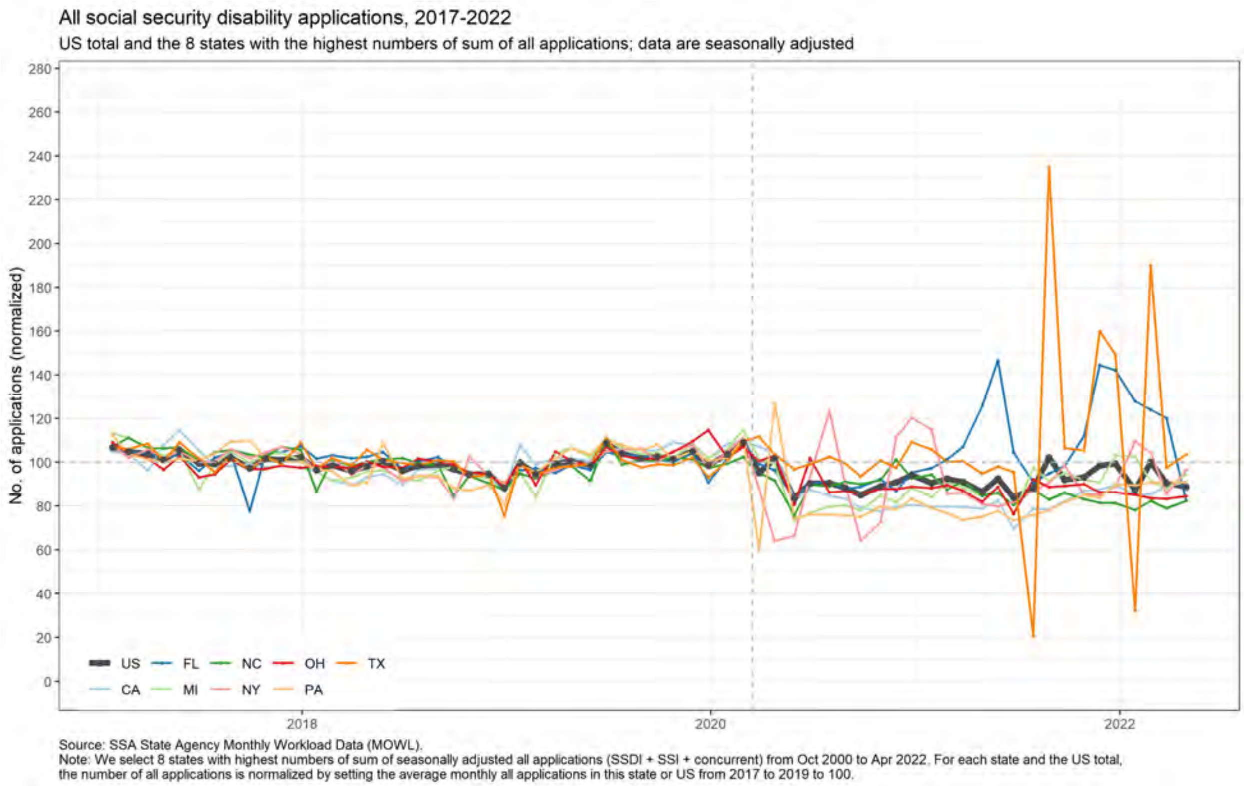


Figure 1a: Trends in total disability applications, 2017-2022

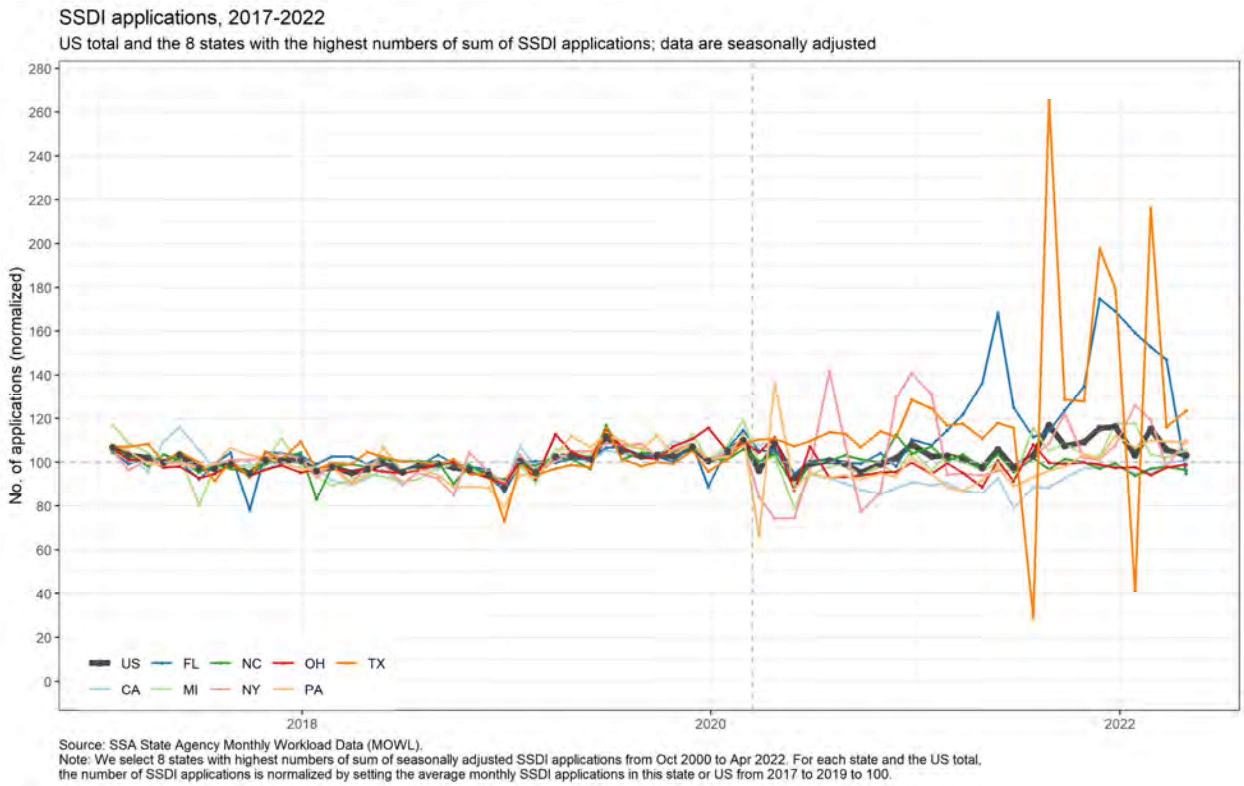


Figure 1b: Trends in SSDI applications, 2017-2022

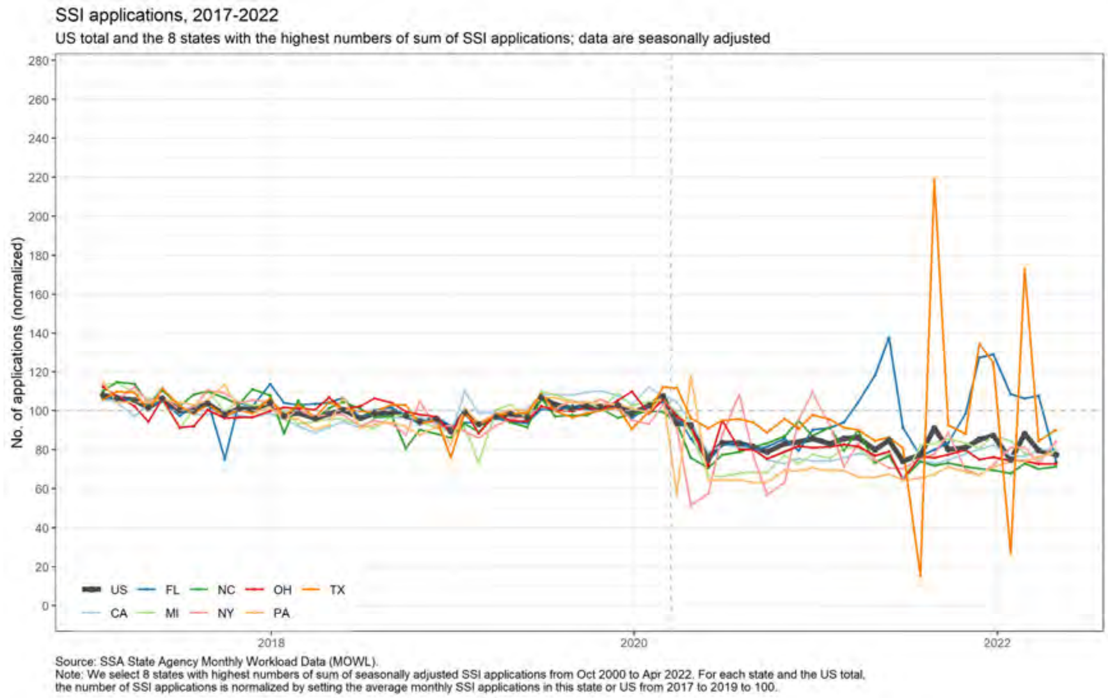


Figure 1c: Trends in SSI applications, 2017-2022

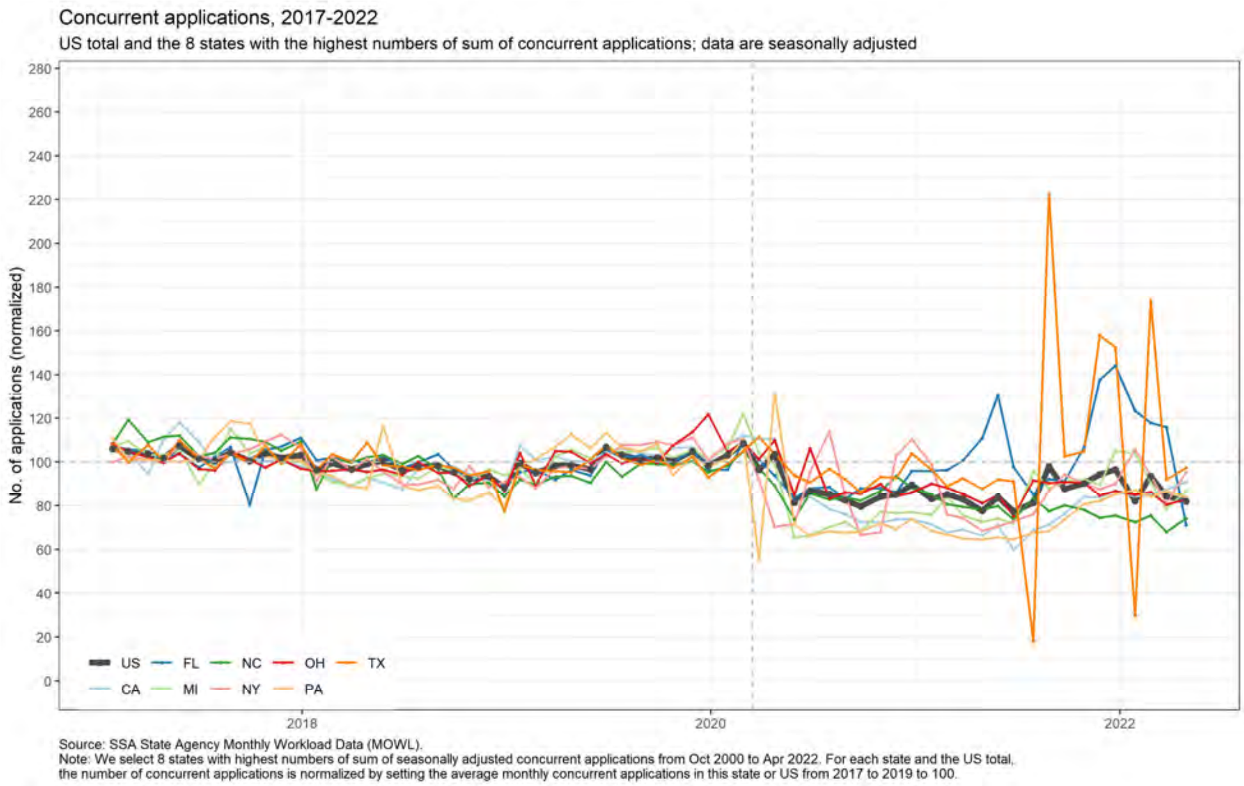


Figure 1d: Trends in concurrent SSI/SSDI applications, 2017-2022

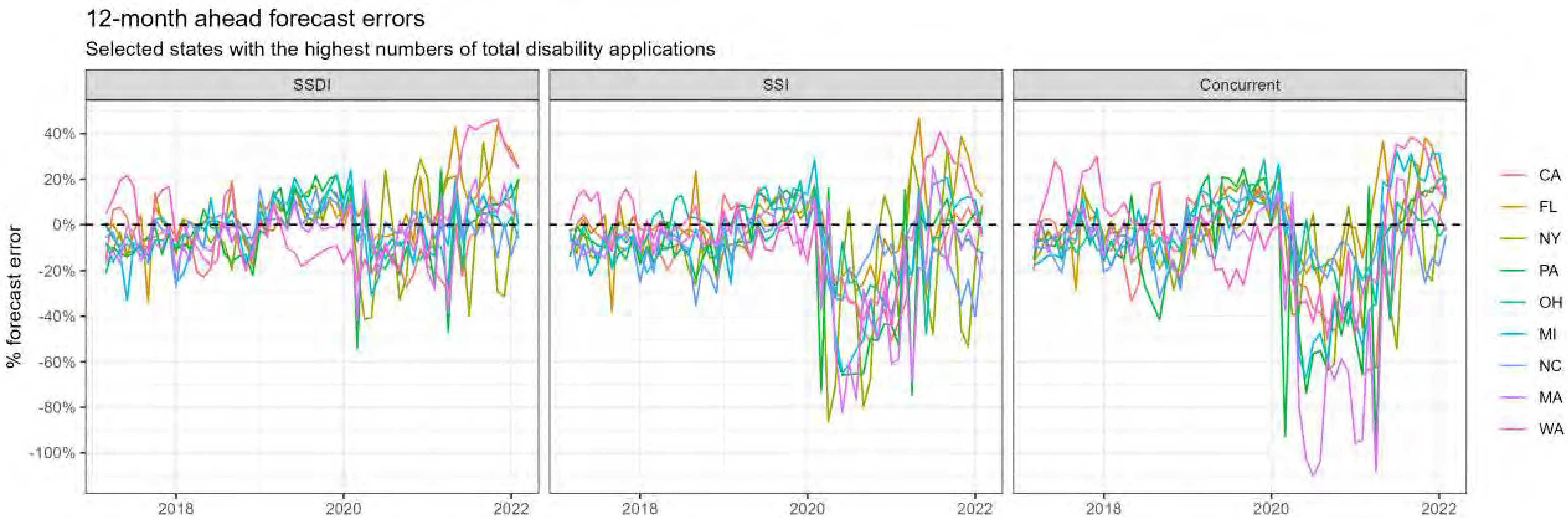


Figure 2: Out-of-sample forecasting errors before and during the pandemic

Notes: Figure shows percentage forecast error for each state shown for January 2018 – April 2022 based on 12-month-ahead forecast errors.

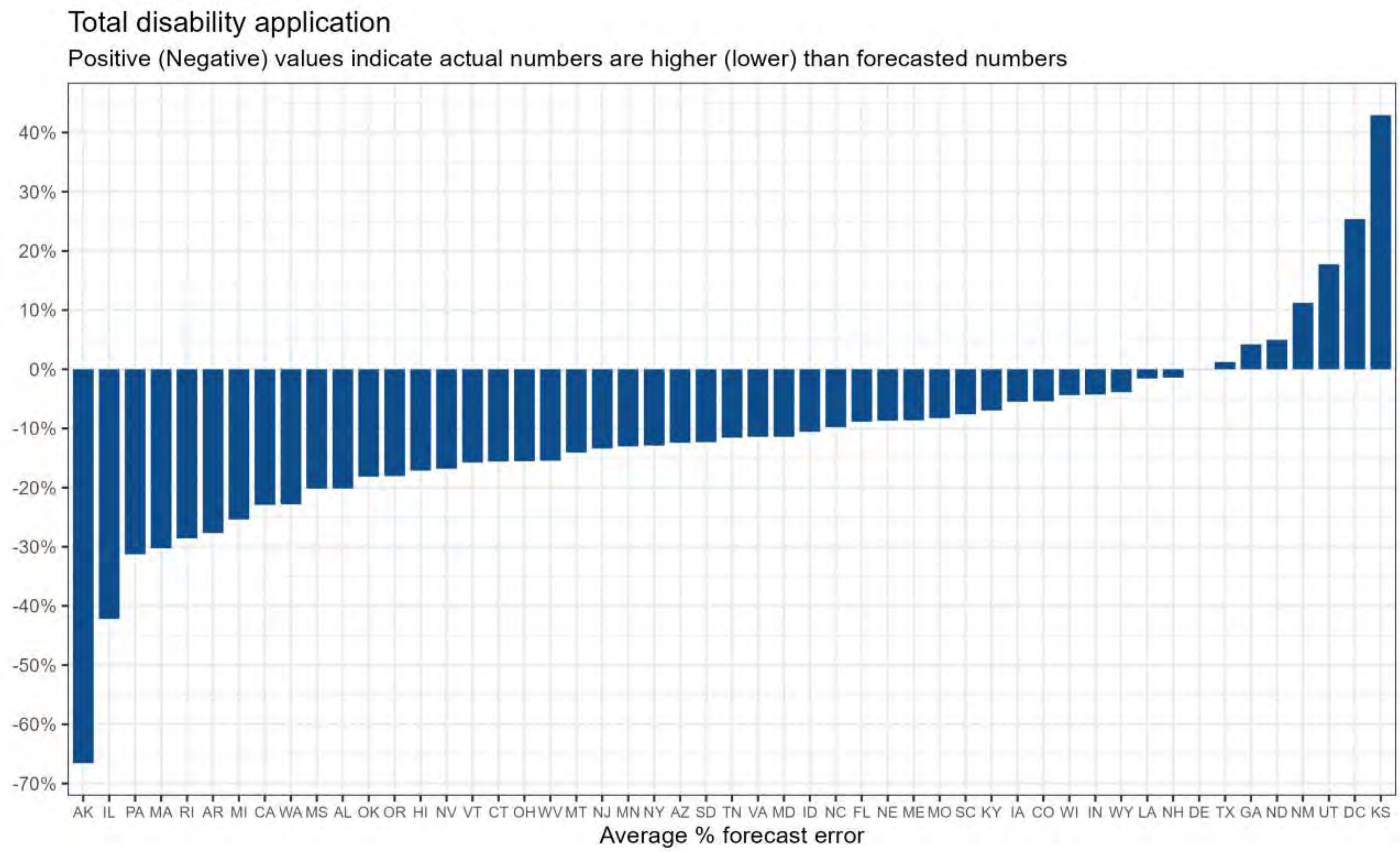


Figure 3: Average forecast error by state for total disability applications, March 2020 – February 2021

Notes: Figure shows average percentage forecast error by state for the time period March 2020 – February 2021 based on 12-month-ahead forecast errors.

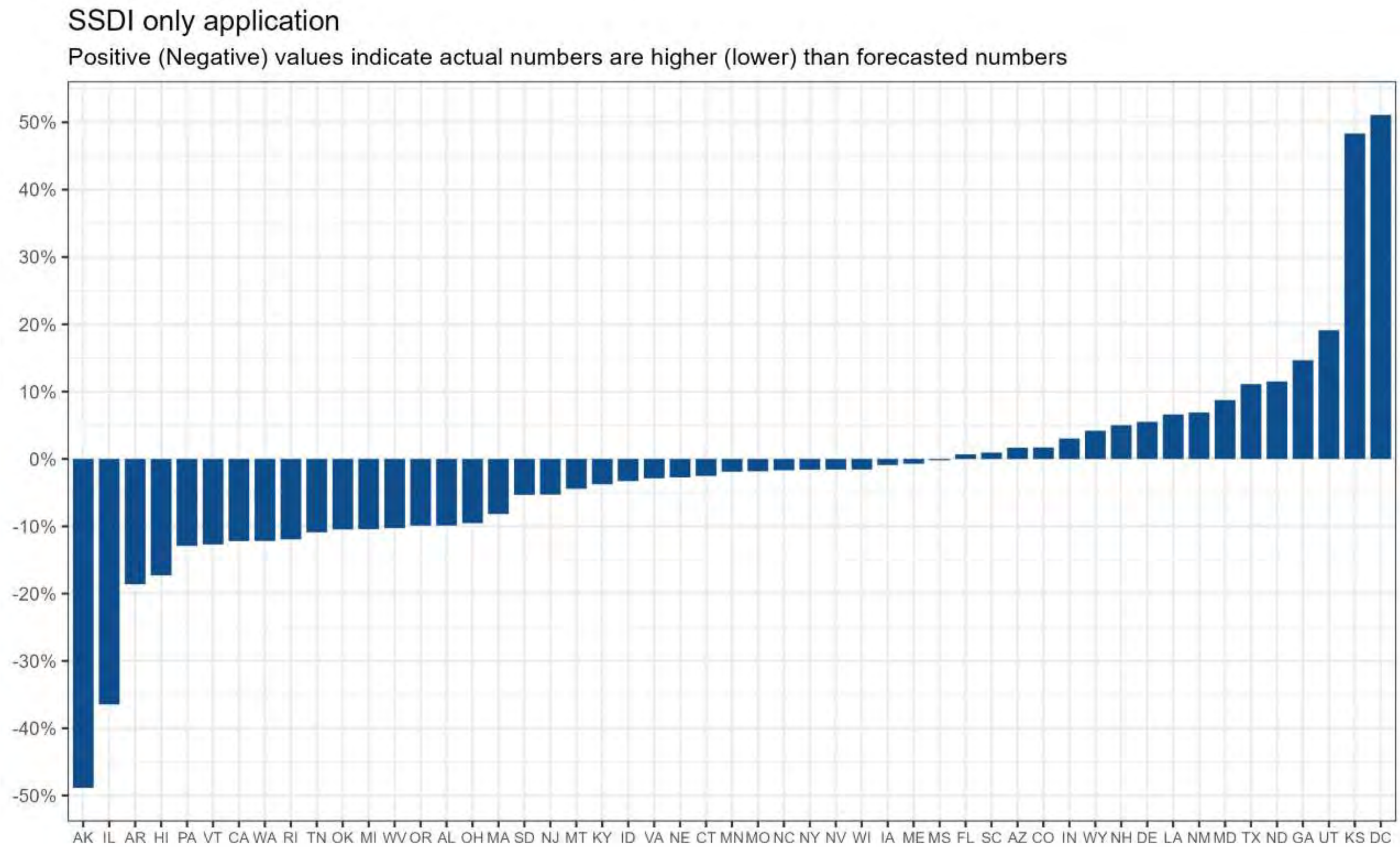


Figure 4: Average forecast error by state for SSDI applications, March 2020 – February 2021

Notes: Figure shows average percentage forecast error by state for the time period March 2020 – February 2021 based on 12-month-ahead forecast errors.

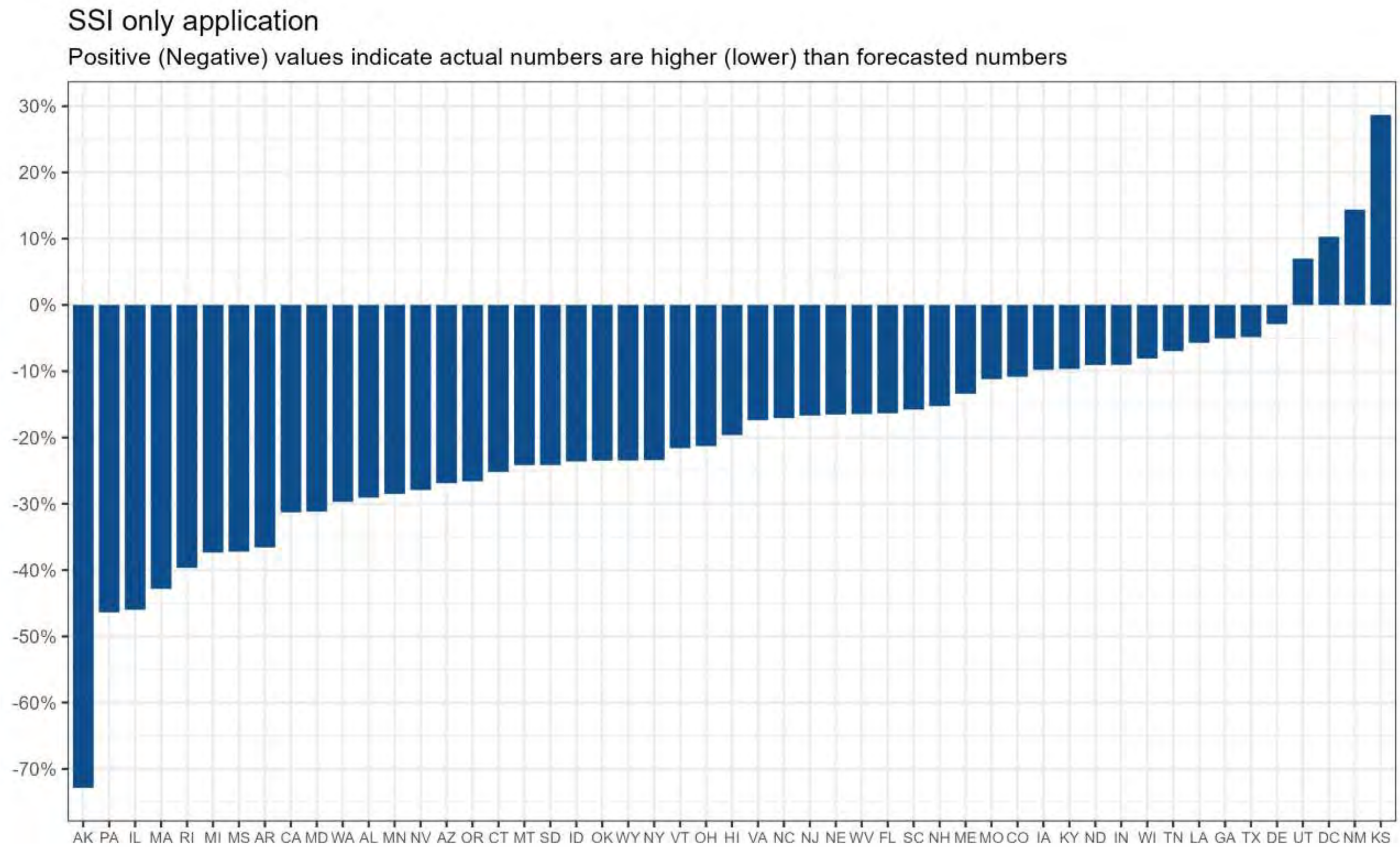


Figure 5: Average forecast error by state for SSI applications, March 2020 – February 2021

Notes: Figure shows average percentage forecast error by state for the time period March 2020 – February 2021 based on 12-month-ahead forecast errors.

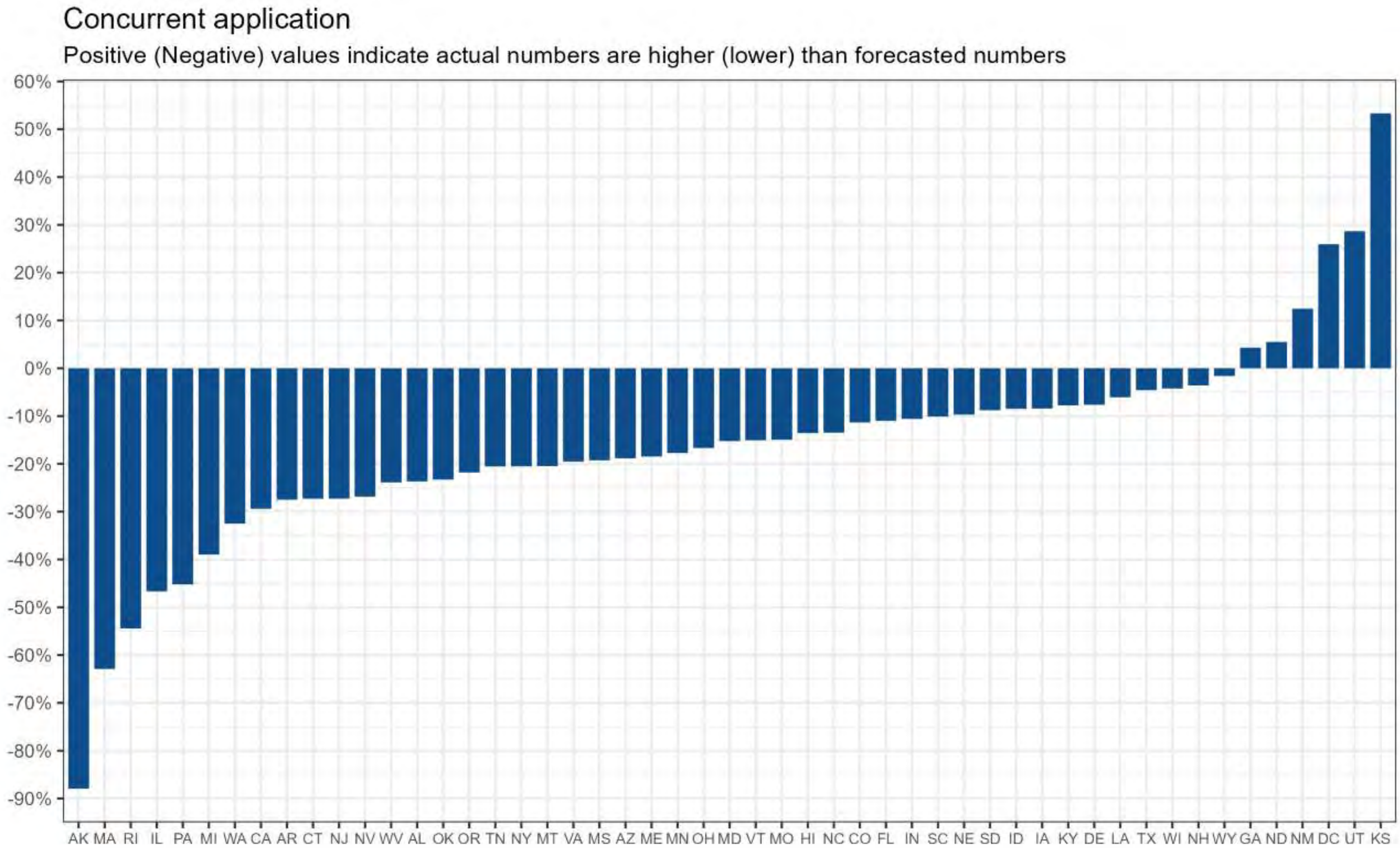


Figure 6: Average forecast error by state for Concurrent applications, March 2020 – February 2021

Notes: Figure shows average percentage forecast error by state for the time period March 2020 – February 2021 based on 12-month-ahead forecast errors.

LIST OF APPENDICES

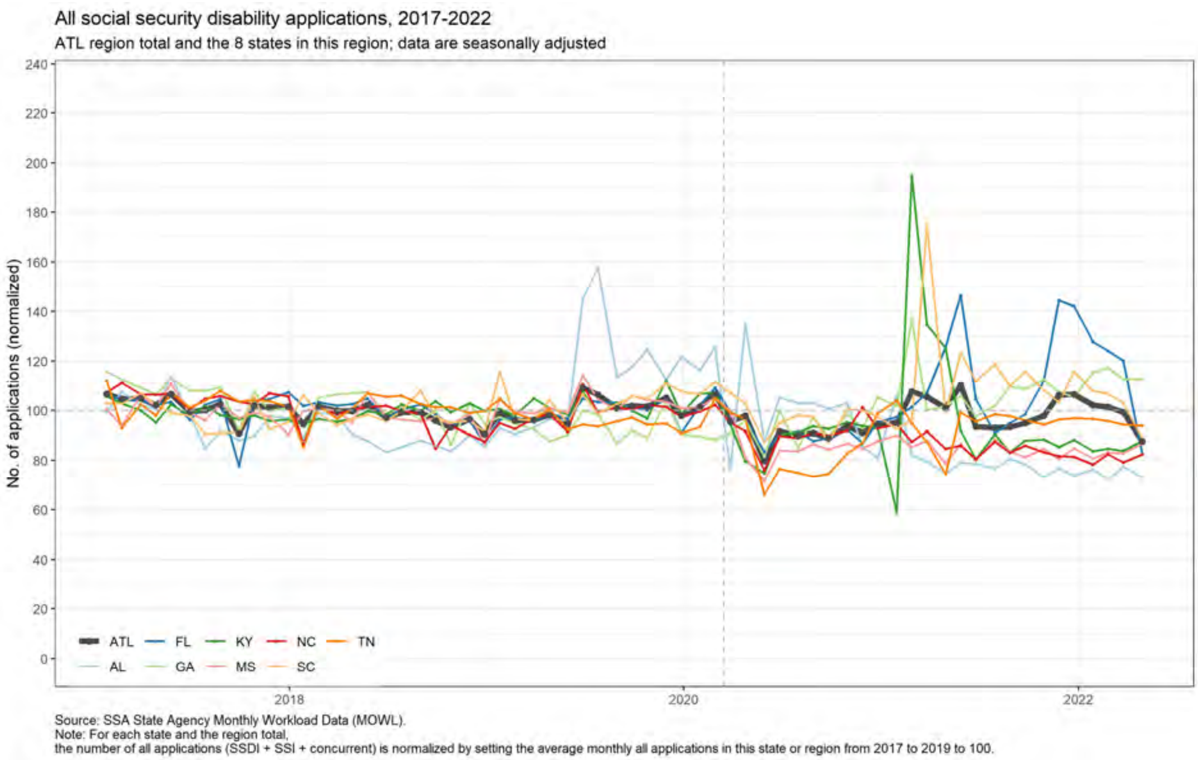
Appendix A: Construction of pandemic-related variable

Variable	Definition	Resources
Dependent variable		
All	Seasonally adjusted number of All kinds of applications	SSA State Agency Monthly Workload Data (https://www.ssa.gov/disability/data/ssa-sa-mowl.htm)
SSDI	Seasonally adjusted number of SSDI only applications	SSA State Agency Monthly Workload Data (https://www.ssa.gov/disability/data/ssa-sa-mowl.htm)
SSI	Seasonally adjusted number of SSI only applications	SSA State Agency Monthly Workload Data (https://www.ssa.gov/disability/data/ssa-sa-mowl.htm)
Concurrent	Seasonally adjusted number of Concurrent applications	SSA State Agency Monthly Workload Data (https://www.ssa.gov/disability/data/ssa-sa-mowl.htm)
COVID policy		
Stay at home	Dummy, =1 if this policy take effect in this month	COVID-19 US State Policies (https://statepolicies.com/data/library/)
Emergency	Dummy, =1 if this policy take effect in this month	
School closure	Dummy, =1 if this policy take effect in this month	
Restaurant closure	Dummy, =1 if this policy take effect in this month	
Other variables		
Post Covic	Dummy, =1 after Feb 2020	
Cum_case	Adjusted cumulative COVID case, adjusted for the number weeks in SSA working months	The Johns Hopkins University's (JHU) Center for System Science and Engineering (CSSE) group's COVID-19 github repository https://github.com/reichlab/covid19-forecast-hub
Cum_death	Adjusted cumulative COVID death, adjusted for the number weeks in SSA working months	The Johns Hopkins University's (JHU) Center for System Science and Engineering (CSSE) group's COVID-19 github repository https://github.com/reichlab/covid19-forecast-hub
High_connect	Dummy, =1 when the states whose broadband internet service are greater than the median level of broadband internet service	American Community Survey in 2020

Meidicaid_ACA	Under Medicaid expansion during this time period	KFF https://www.kff.org/medicaid/issue-brief/status-of-state-medicaid-expansion-decisions-interactive-map/
Group1	Dummy, =1 for states AK, ID, KS, NE, NV, OR, UT	
Group2	Dummy, =1 for states CT, HI, IL, MN, MO, NH, ND, OK, VA	
Controls		
Unemply_rate	Seasonally adjusted unemployment rate	BLS

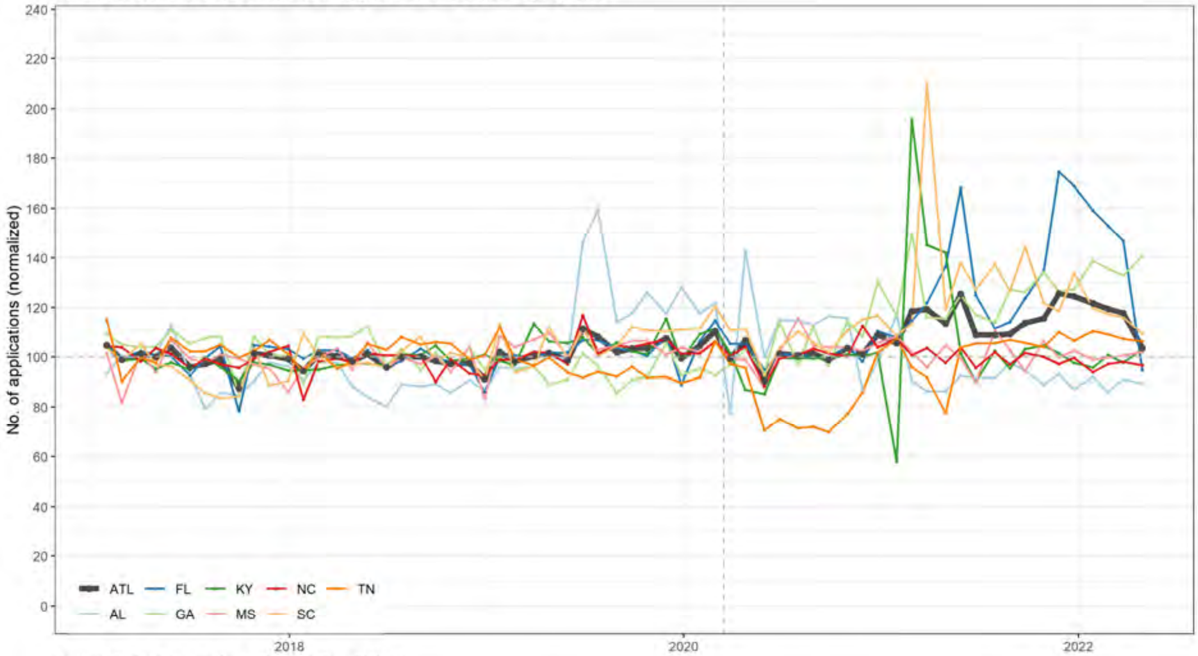
Appendix B: SSA region figures

a) ATL (Atlanta) region



SSDI applications, 2017-2022

ATL region total and the 8 states in this region; data are seasonally adjusted

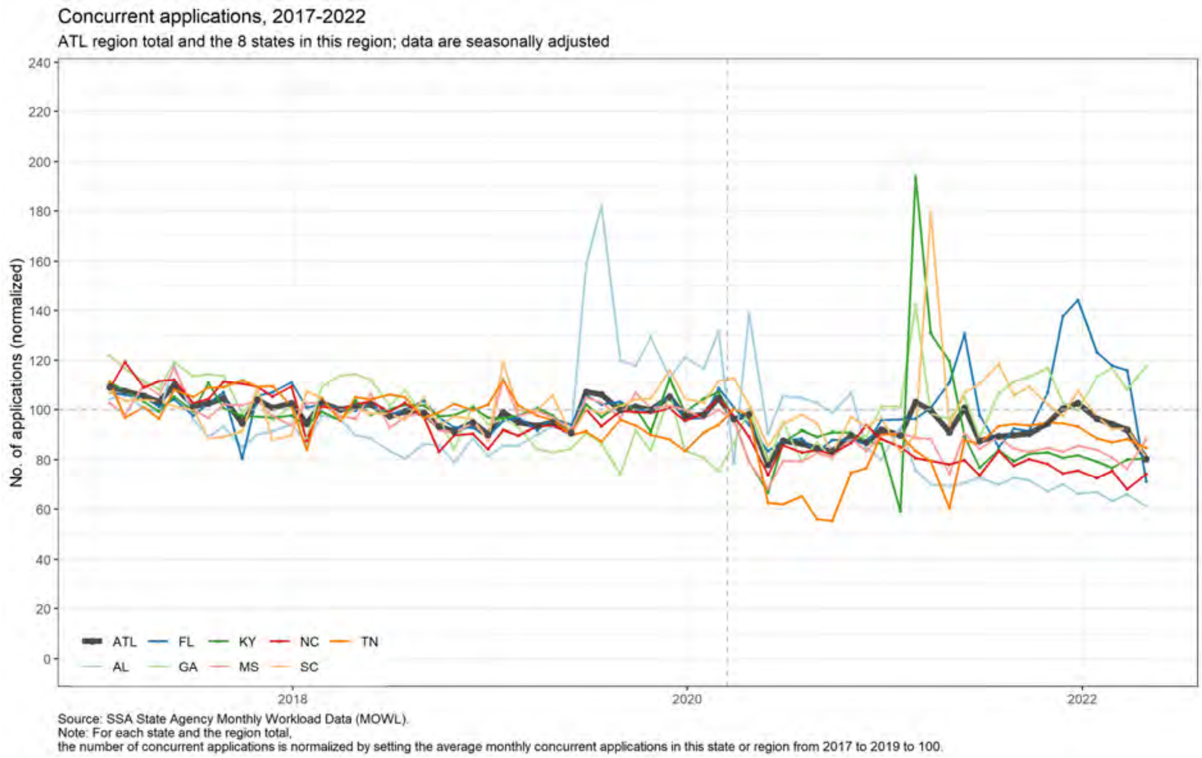


Source: SSA State Agency Monthly Workload Data (MOWL).
Note: For each state and the region total,
the number of SSDI applications is normalized by setting the average monthly SSDI applications in this state or region from 2017 to 2019 to 100.

SSI applications, 2017-2022

ATL region total and the 8 states in this region; data are seasonally adjusted

Source: SSA State Agency Monthly Workload Data (MOWL).
Note: For each state and the region total,
the number of SSI applications is normalized by setting the average monthly SSI applications in this state or region from 2017 to 2019 to 100.

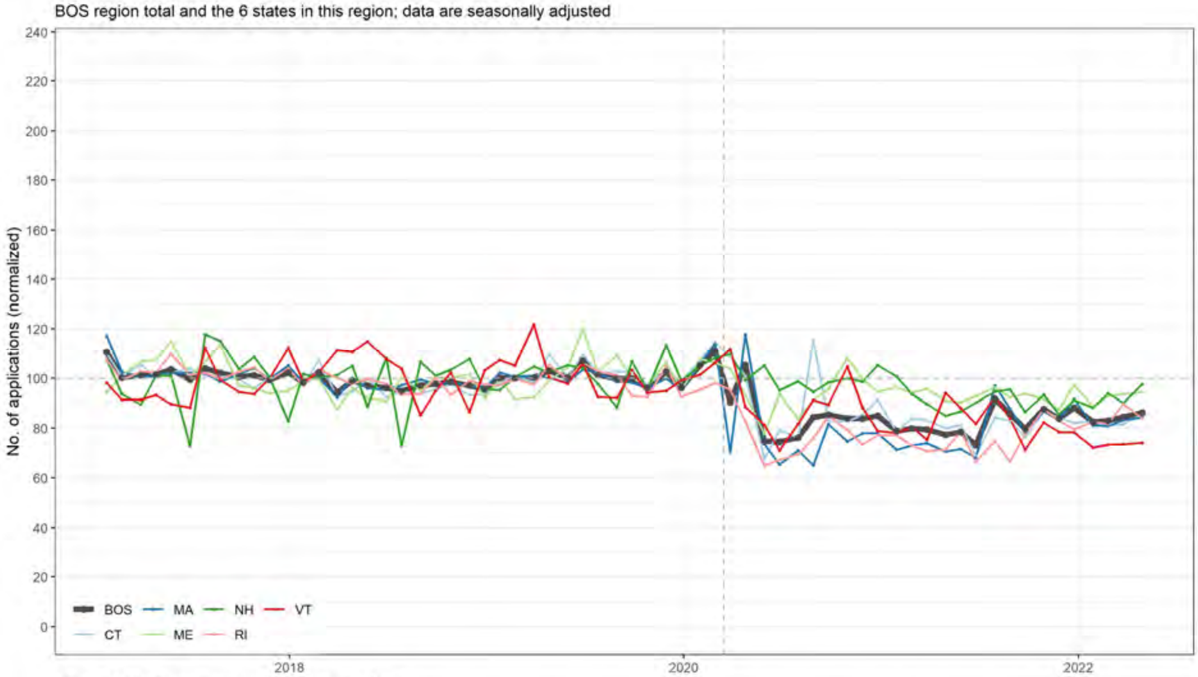


In general, states in the ATL region show a downward trend in SSDI, SSI, and concurrent applications during the start of COVID before turning to a peak and growth in early 2021 and late 2021.

b) BOS (Boston) region

Total social security disability applications, 2017-2022

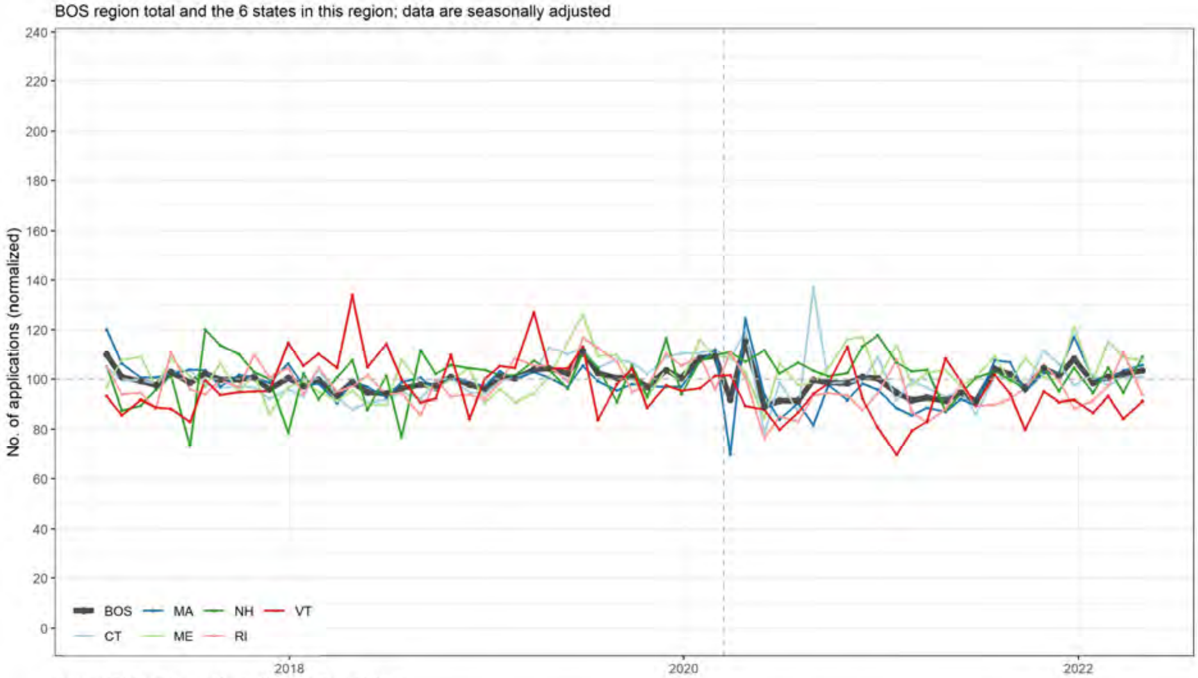
BOS region total and the 6 states in this region; data are seasonally adjusted



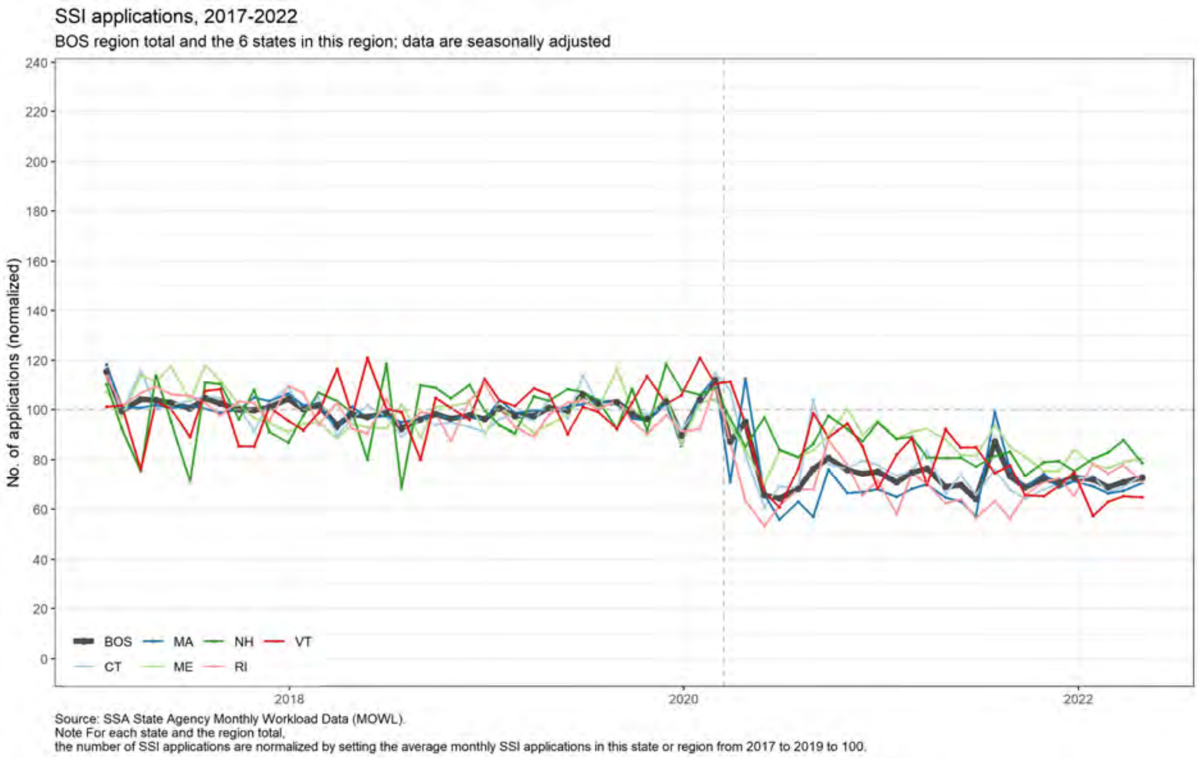
Source: SSA State Agency Monthly Workload Data (MOWL).
Note For each state and the region total,
the number of all applications (SSDI + SSI + concurrent) are normalized by setting the average monthly all applications in this state or region from 2017 to 2019 to 100.

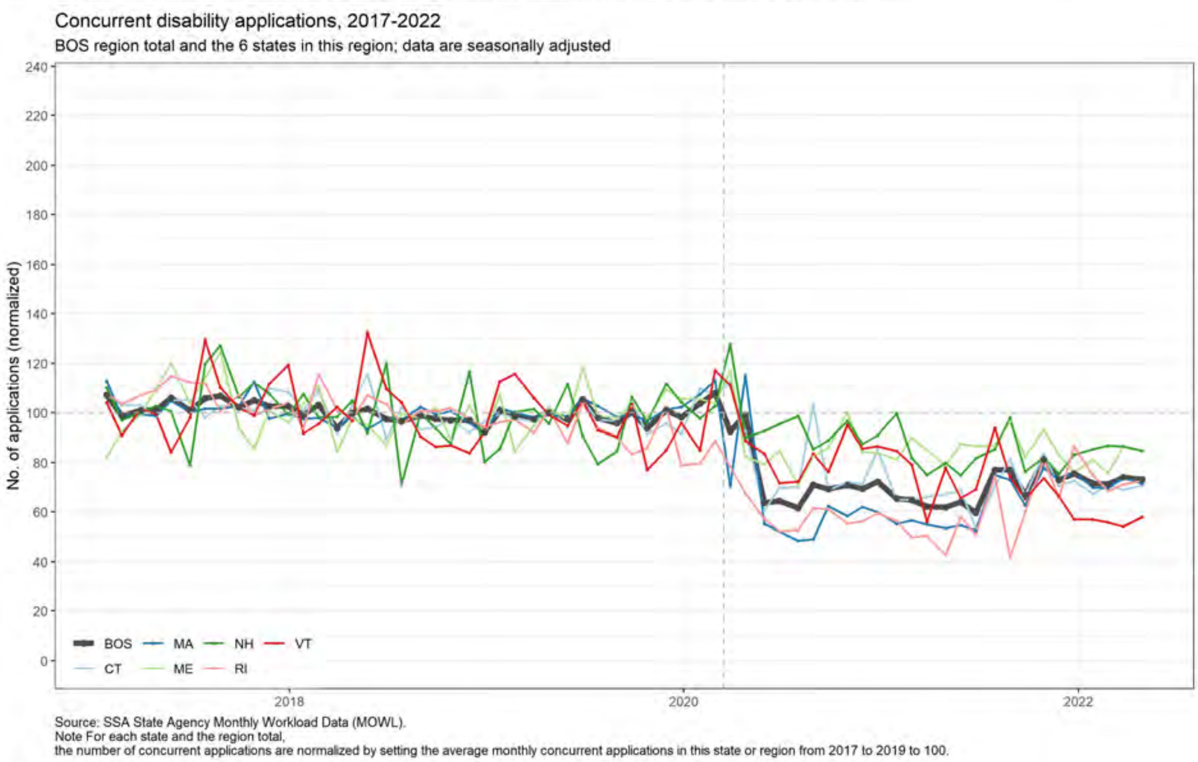
SSDI applications, 2017-2022

BOS region total and the 6 states in this region; data are seasonally adjusted



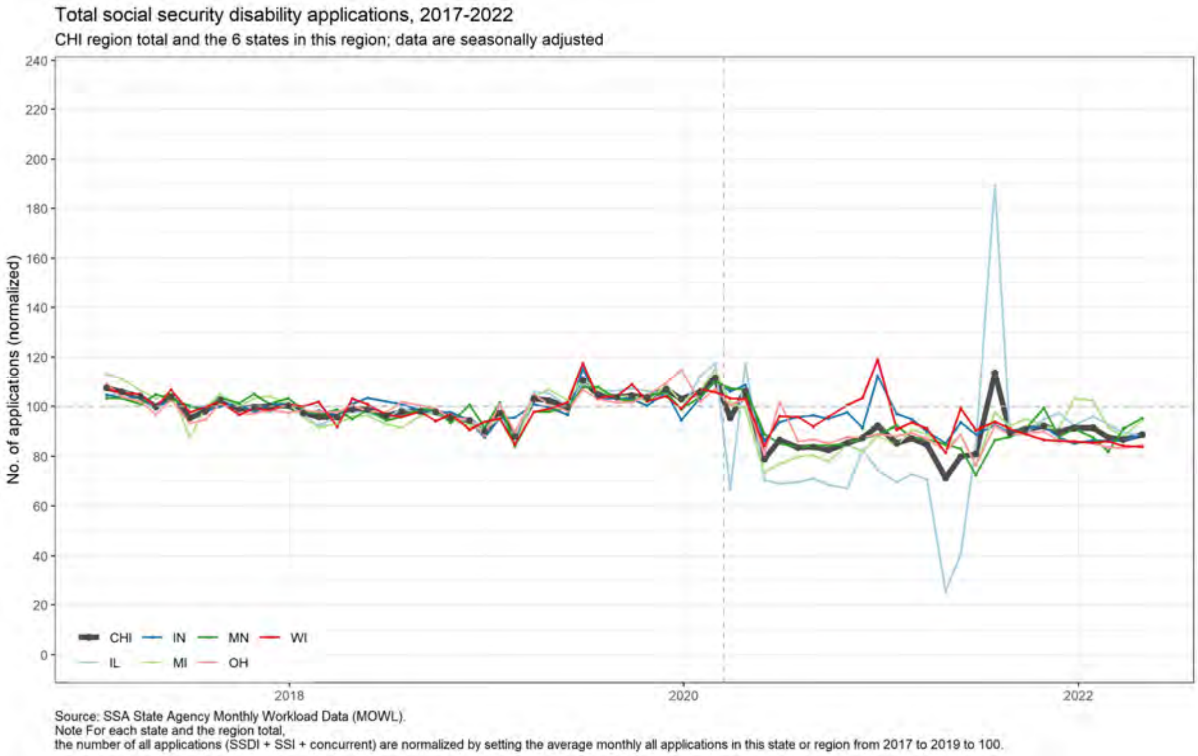
Source: SSA State Agency Monthly Workload Data (MOWL).
Note For each state and the region total,
the number of SSDI applications are normalized by setting the average monthly SSDI applications in this state or region from 2017 to 2019 to 100.

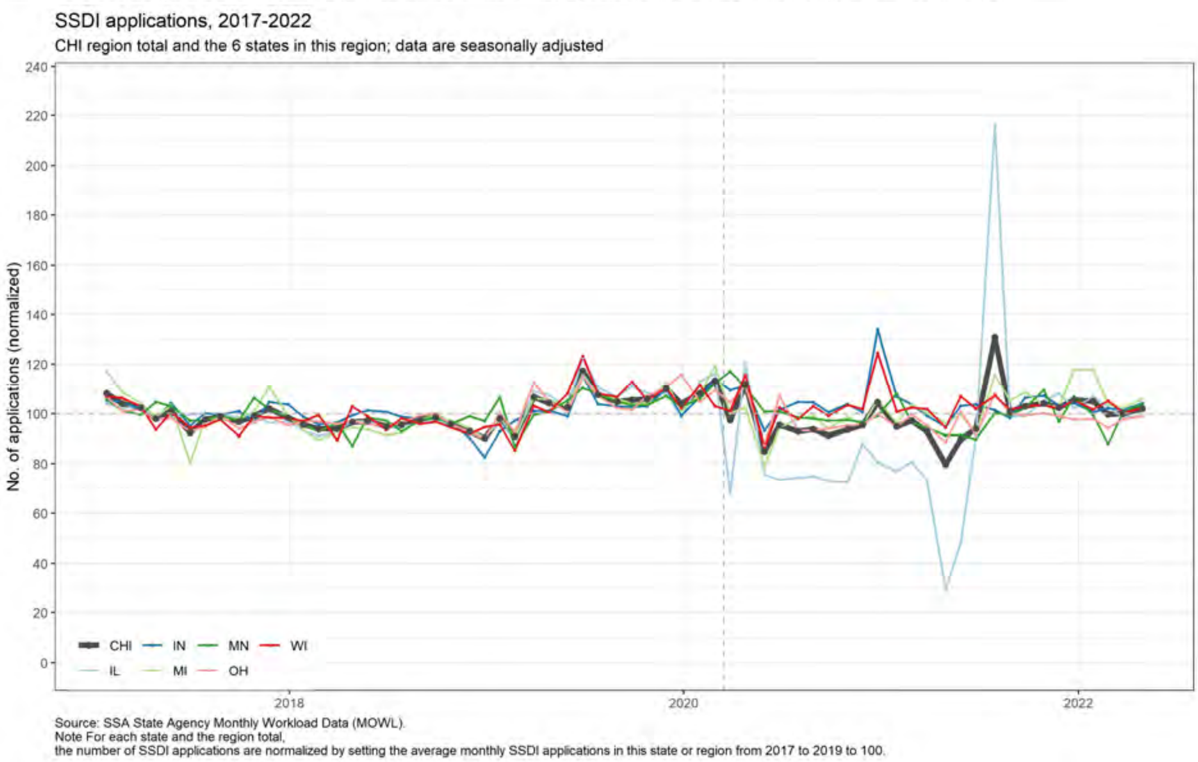




SSDI, SSI and concurrent applications show a significant decline at the beginning of the pandemic in the BOS area states. Thereafter, they turn to remain stable relatively.

c) CHI (Chicago) region





SSI applications, 2017-2022

CHI region total and the 6 states in this region; data are seasonally adjusted

Source: SSA State Agency Monthly Workload Data (MOWL).
Note For each state and the region total,
the number of SSI applications are normalized by setting the average monthly SSI applications in this state or region from 2017 to 2019 to 100.

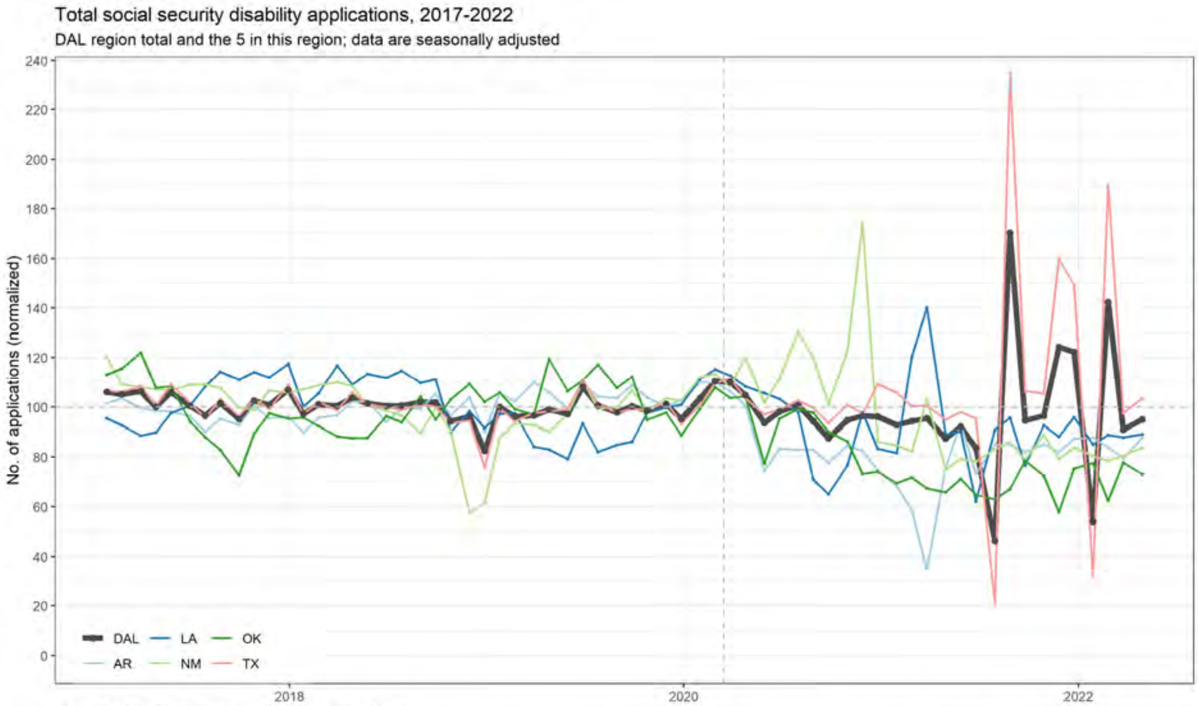
Concurrent disability applications, 2017-2022

CHI region total and the 6 states in this region; data are seasonally adjusted

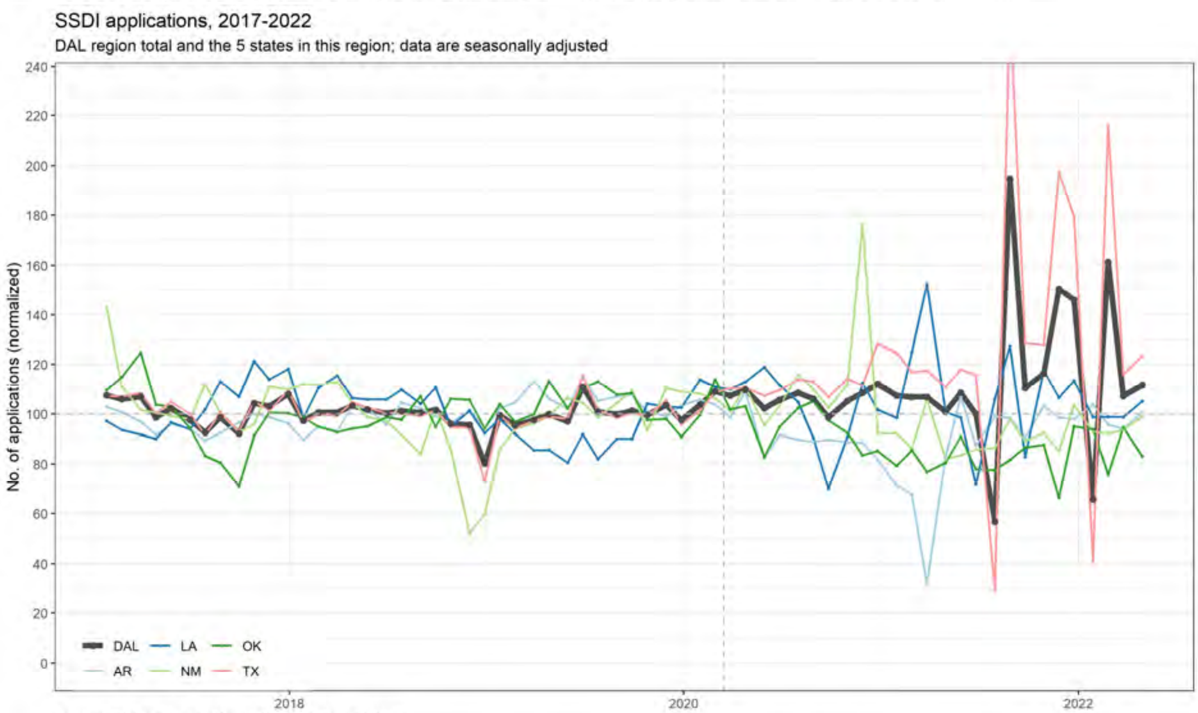
Source: SSA State Agency Monthly Workload Data (MOWL).
Note For each state and the region total,
the number of concurrent applications are normalized by setting the average monthly concurrent applications in this state or region from 2017 to 2019 to 100.

States in the CHI region have different patterns in these three applications. In addition to the common declining characteristics at the beginning of the pandemic, they experience a sharp decline followed by a sharp rise in mid-2021, coinciding with the expiration of some emergency declarations.

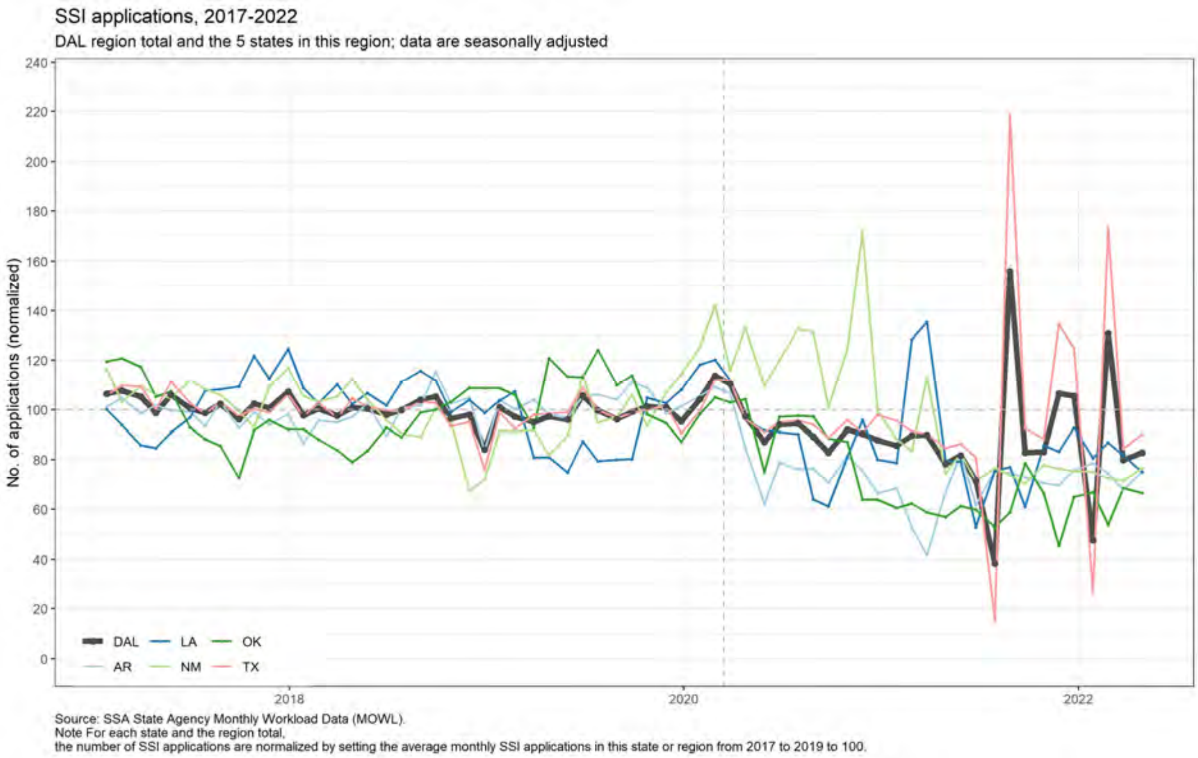
d) DAL (Dallas) region

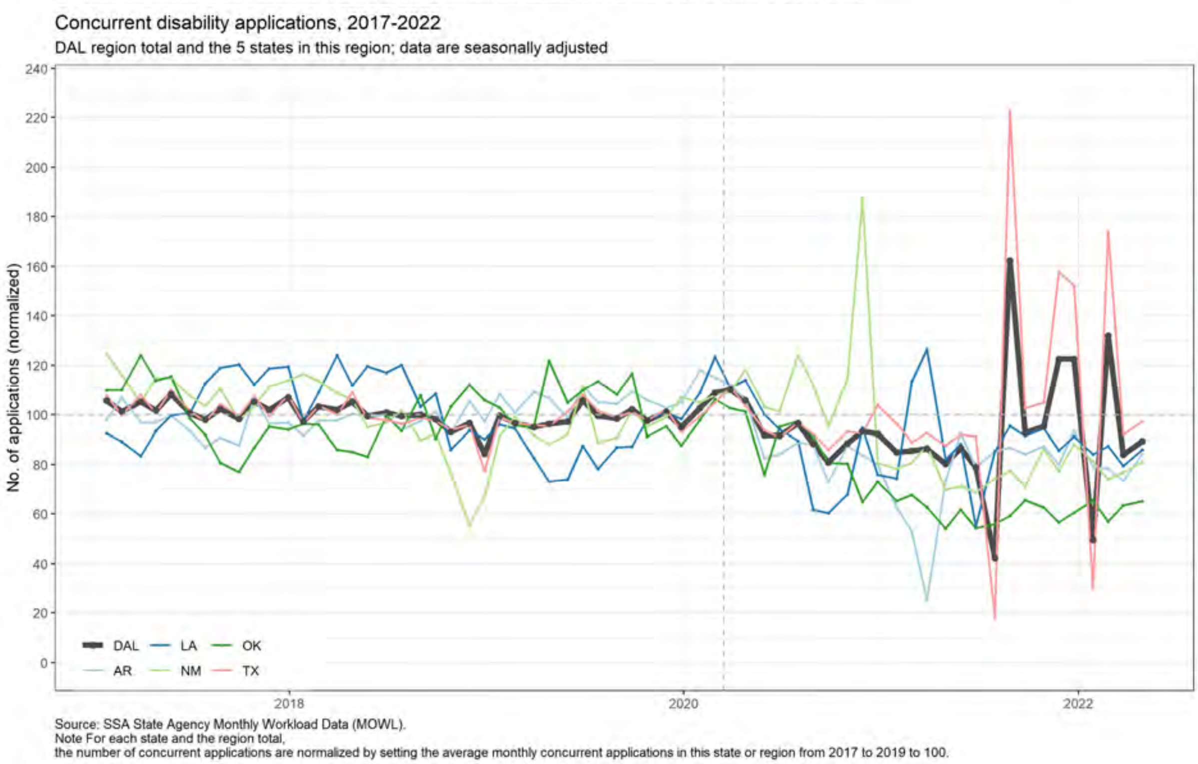


Source: SSA State Agency Monthly Workload Data (MOWL).
Note For each state and the region total,
the number of all applications (SSDI + SSI + cooncurrent) are normalized by setting the average monthly all applications in this state or region from 2017 to 2019 to 100.



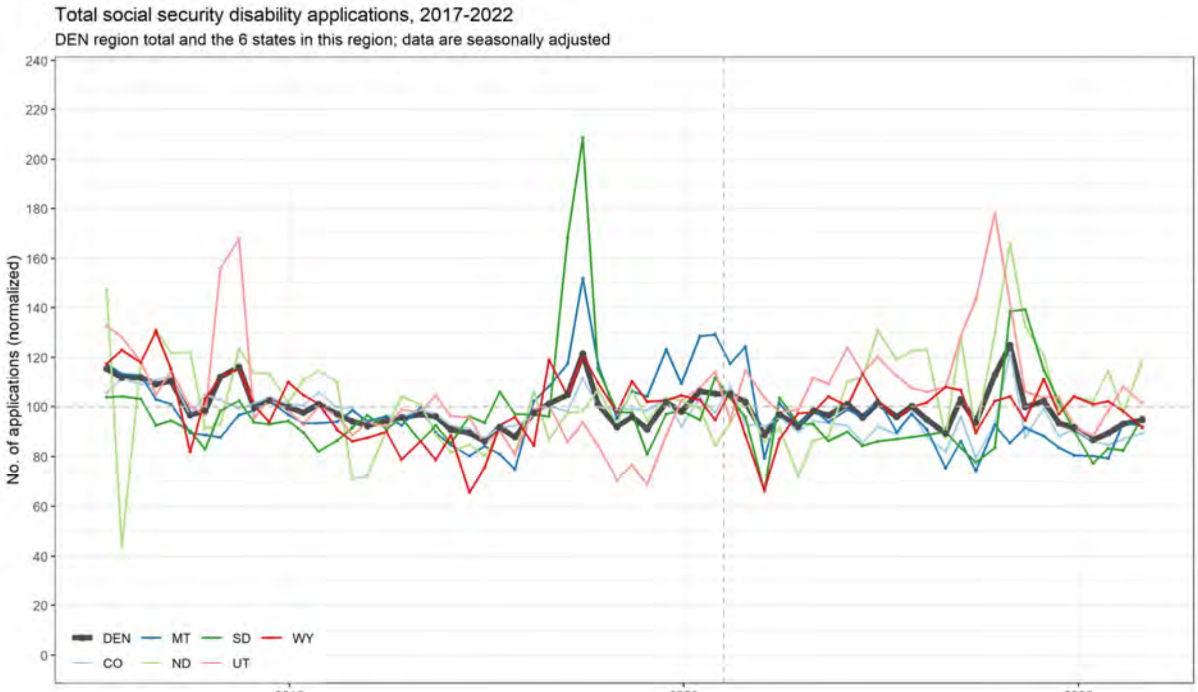
Source: SSA State Agency Monthly Workload Data (MOWL).
Note For each state and the region total,
the number of SSDI applications are normalized by setting the average monthly SSDI applications in this state or region from 2017 to 2019 to 100.



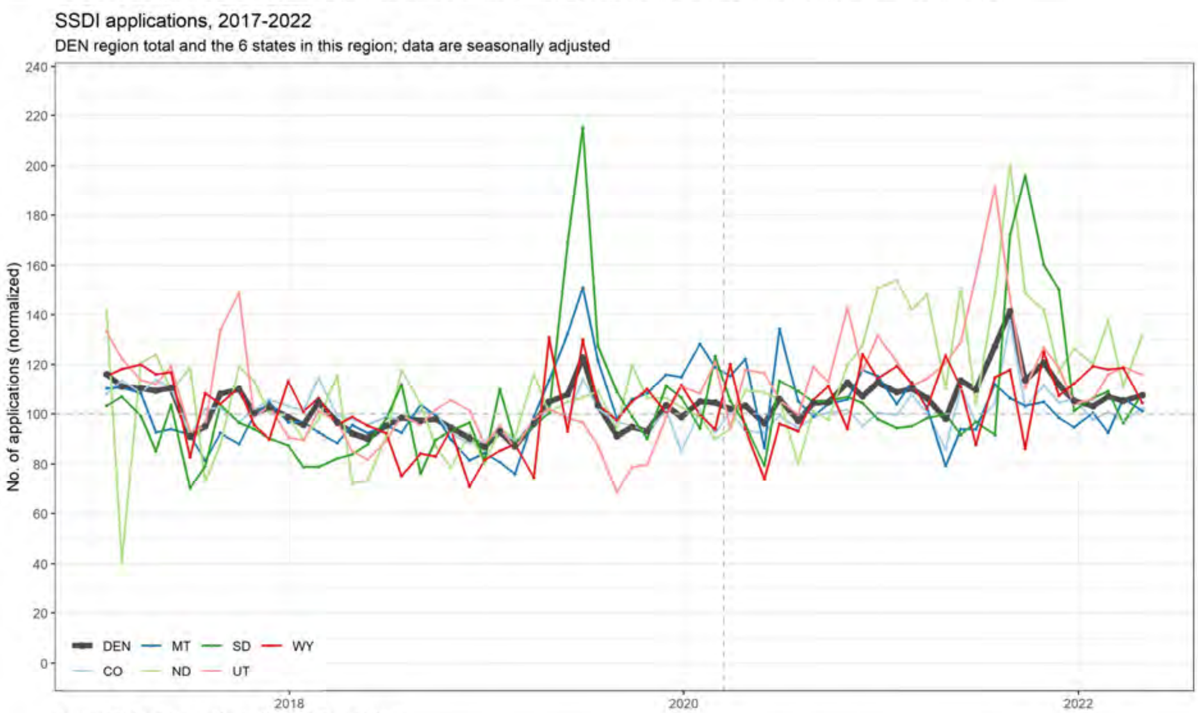


In states in the DAL region, particularly in Texas and New Mexico, SSDI, SSI, and concurrent applications show considerable fluctuations during the pandemic.

e) DEN (Denver) region



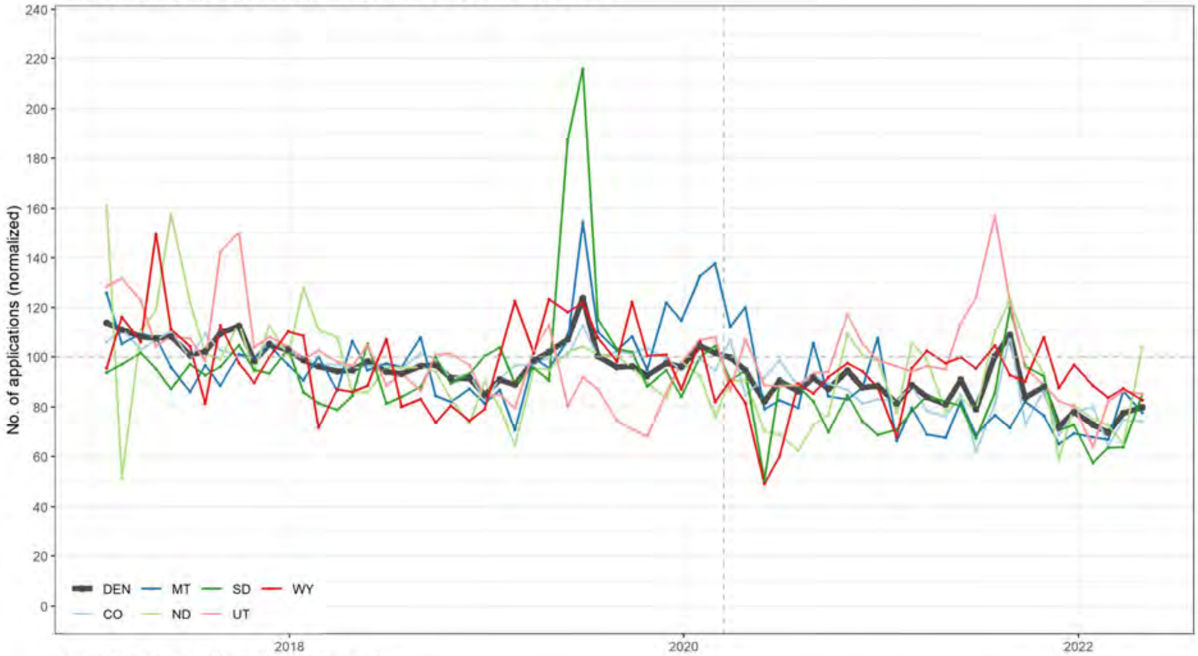
Source: SSA State Agency Monthly Workload Data (MOWL).
Note For each state and the region total,
the number of all applications (SSDI + SSI + concurrent) are normalized by setting the average monthly all applications in this state or region from 2017 to 2019 to 100.



Source: SSA State Agency Monthly Workload Data (MOWL).
Note For each state and the region total,
the number of SSDI applications are normalized by setting the average monthly SSDI applications in this state or region from 2017 to 2019 to 100.

SSI applications, 2017-2022

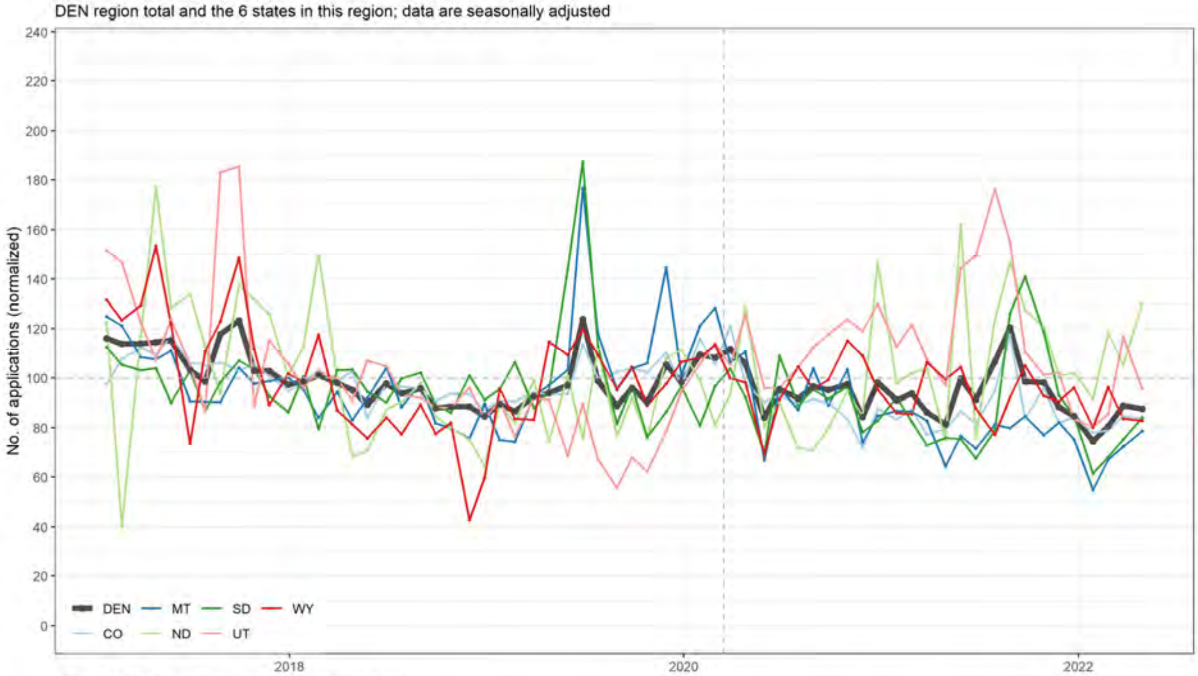
DEN region total and the 6 states in this region; data are seasonally adjusted



Source: SSA State Agency Monthly Workload Data (MOWL).
Note For each state and the region total,
the number of SSI applications are normalized by setting the average monthly SSI applications in this state or region from 2017 to 2019 to 100.

Concurrent disability applications, 2017-2022

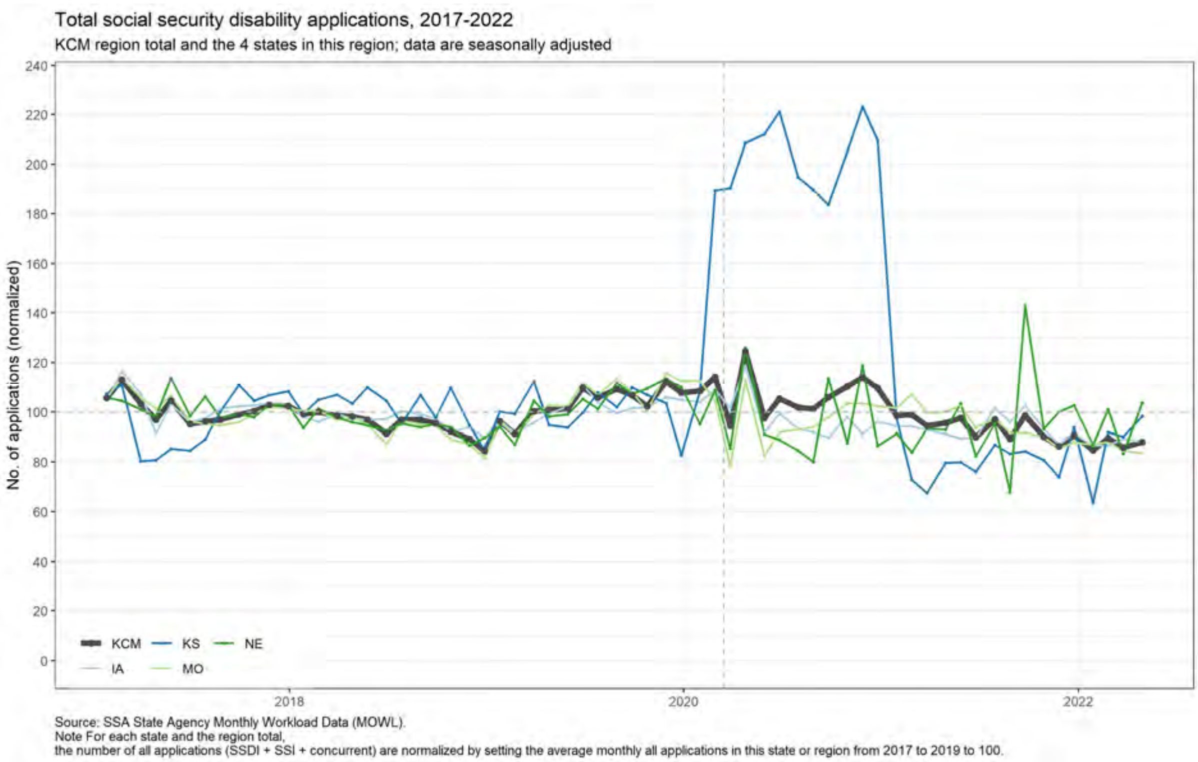
DEN region total and the 6 states in this region; data are seasonally adjusted



Source: SSA State Agency Monthly Workload Data (MOWL).
Note For each state and the region total,
the number of concurrent applications are normalized by setting the average monthly concurrent applications in this state or region from 2017 to 2019 to 100.

Among states in the DEN region, SSDI, SSI, and concurrent applications show similar fluctuations during the pandemic as before the pandemic and peak in the third quarter of 2021.

f) KCM (Kansas City) region



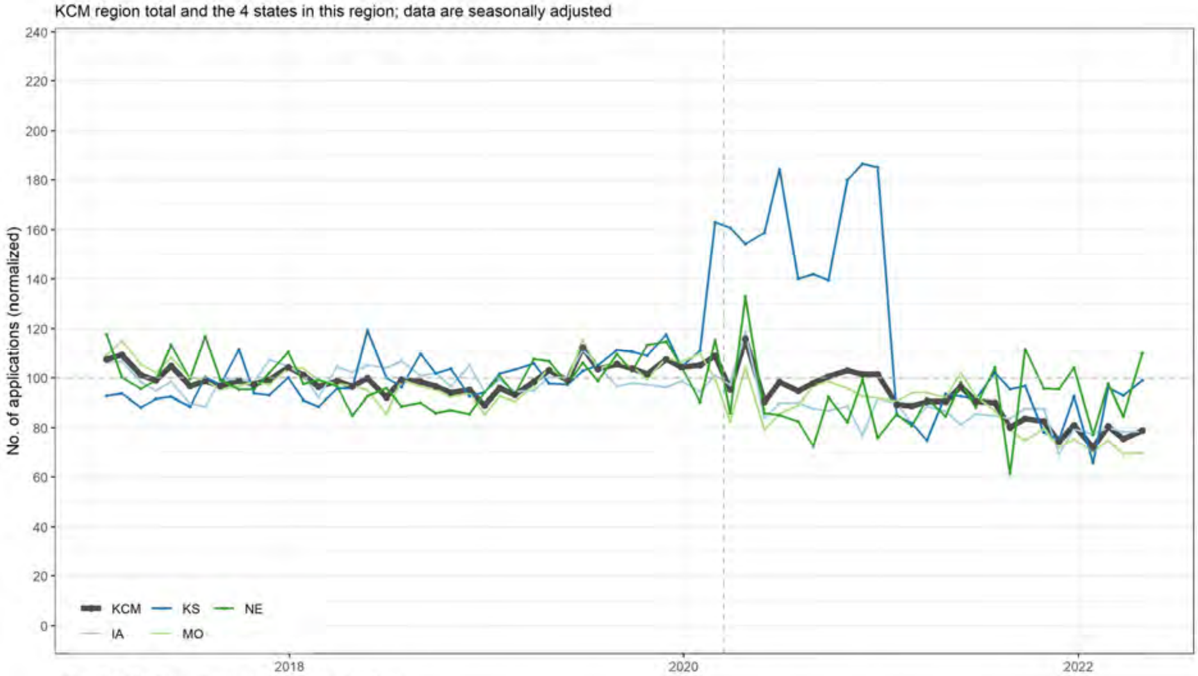
SSDI applications, 2017-2022

KCM region total and the 4 states in this region; data are seasonally adjusted

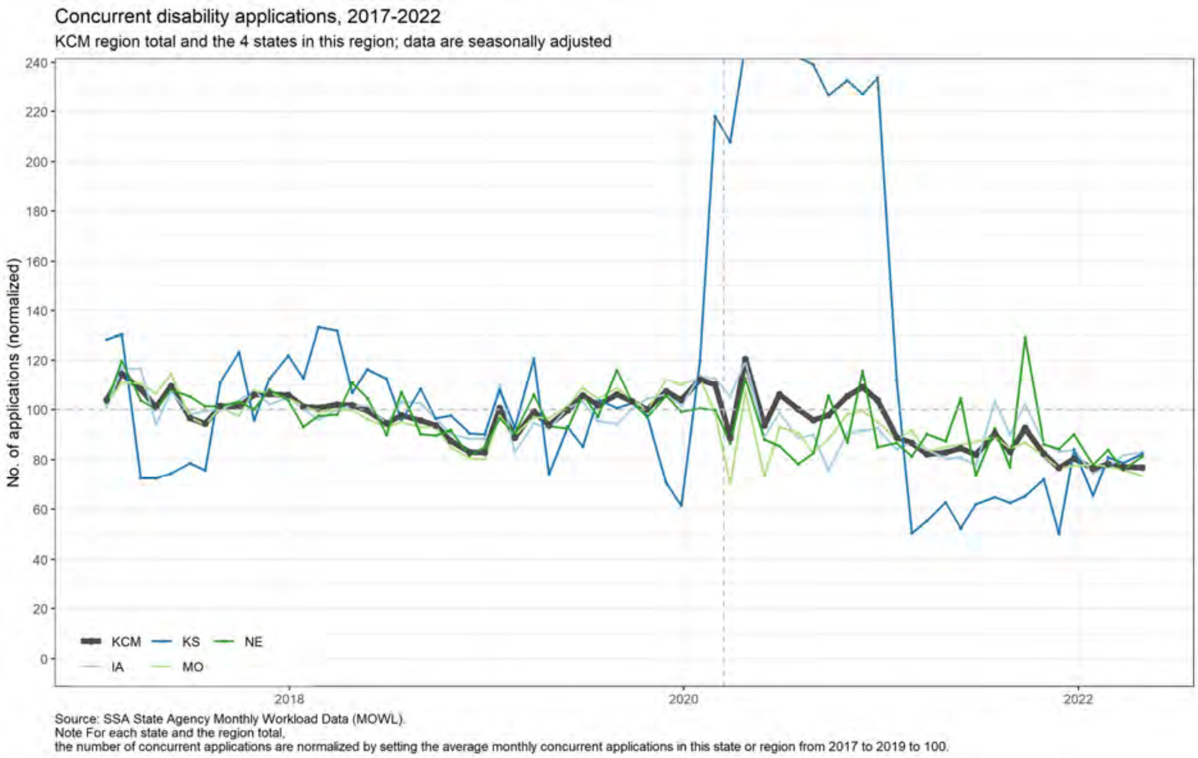
Source: SSA State Agency Monthly Workload Data (MOWL).
Note For each state and the region total,
the number of SSDI applications are normalized by setting the average monthly SSDI applications in this state or region from 2017 to 2019 to 100.

SSI applications, 2017-2022

KCM region total and the 4 states in this region; data are seasonally adjusted



Source: SSA State Agency Monthly Workload Data (MOWL).
Note For each state and the region total,
the number of SSI applications are normalized by setting the average monthly SSI applications in this state or region from 2017 to 2019 to 100.

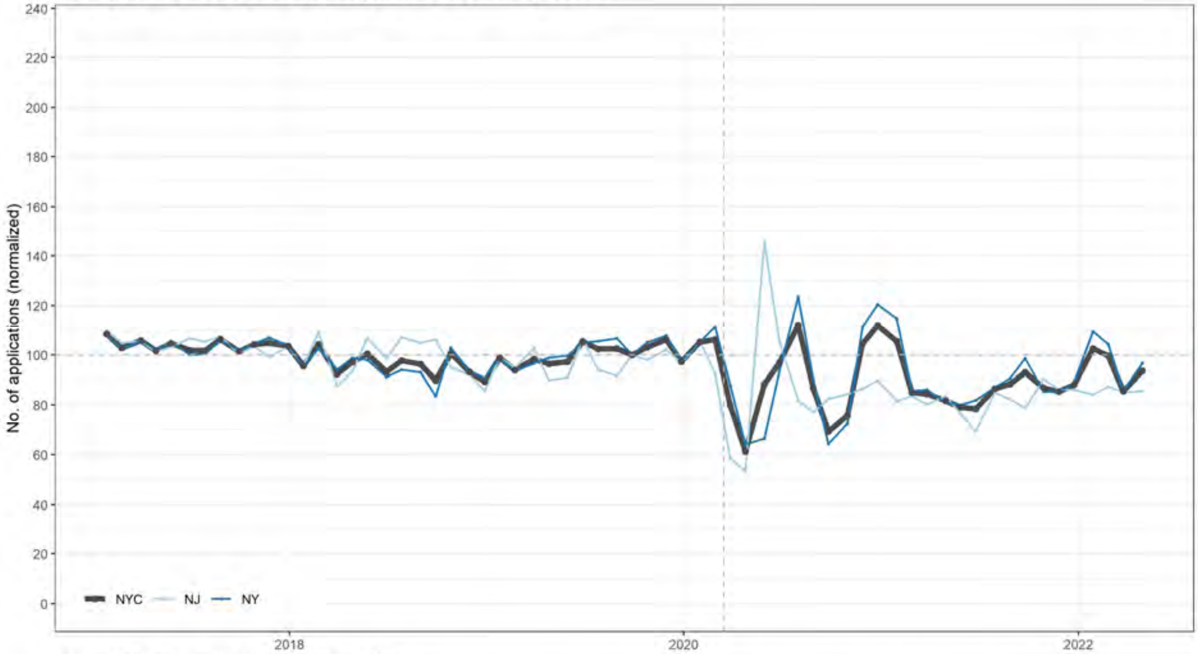


All states in the KCM region, except KS, have had steady SSDI, SSI, and concurrent applications since March 2020. Kansas applications grow rapidly in 2020 and fall off a cliff in early 2021.

g) NYC (New York) region

Total social security disability applications, 2017-2022

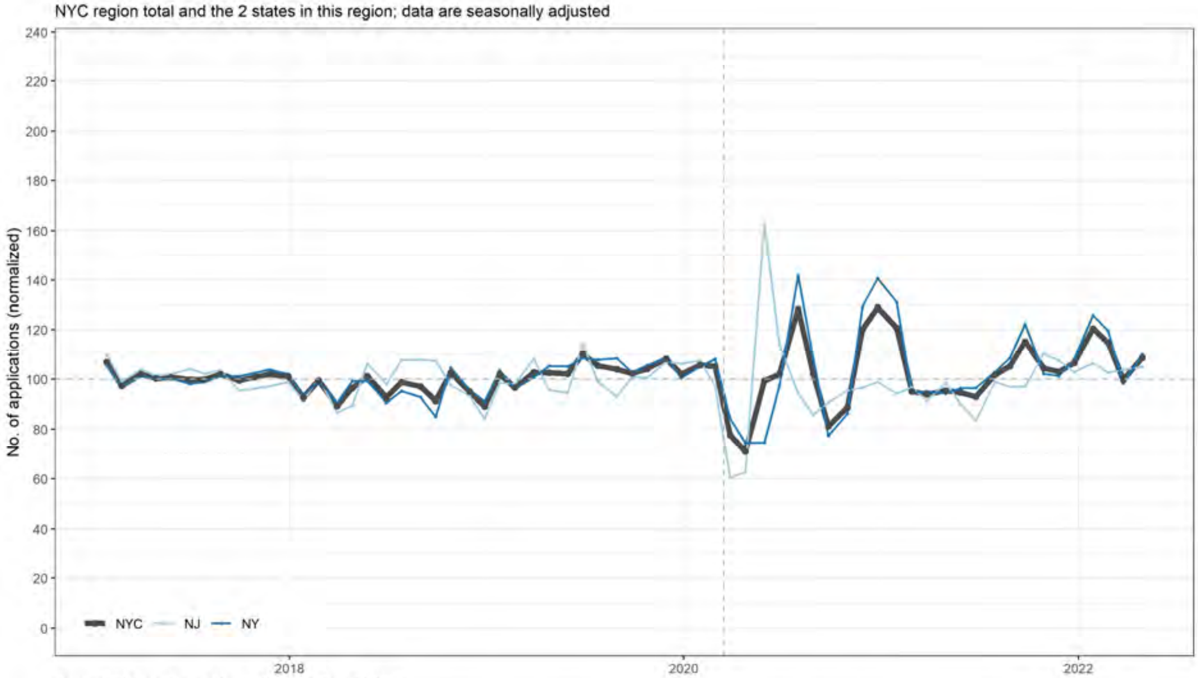
NYC region total and the 2 states in this region; data are seasonally adjusted



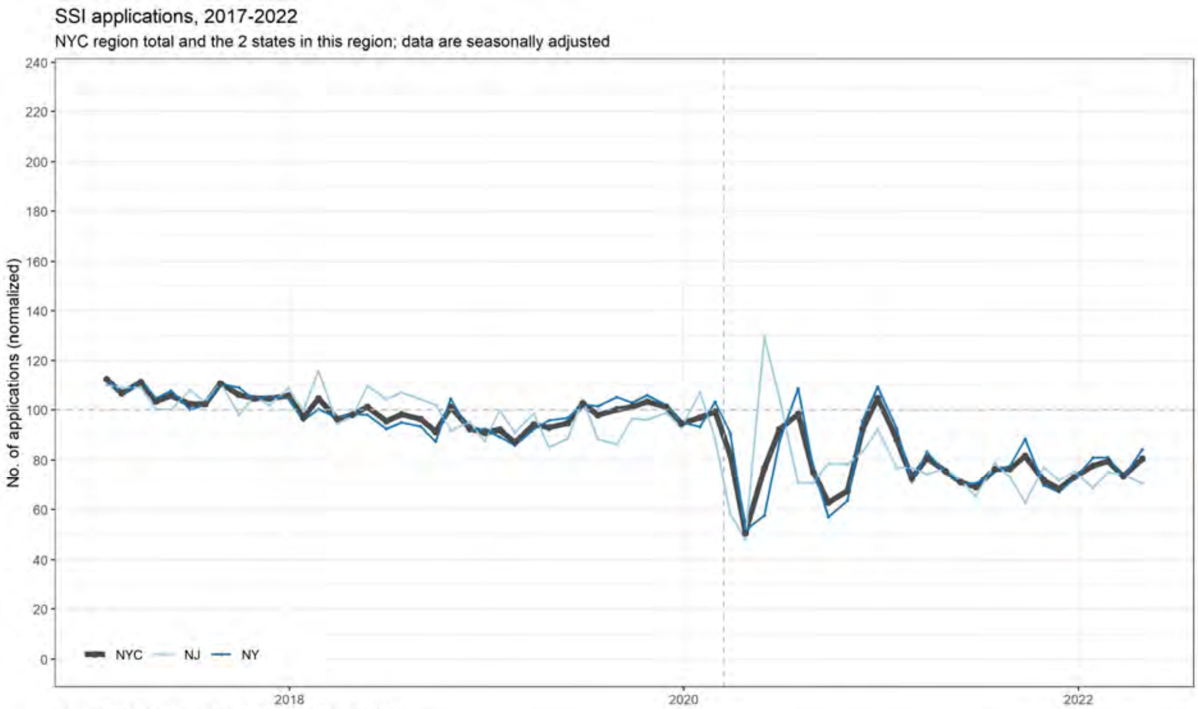
Source: SSA State Agency Monthly Workload Data (MOWL).
Note For each state and the region total,
the number of all applications (SSDI + SSI + concurrent) are normalized by setting the average monthly all applications in this state or region from 2017 to 2019 to 100.

SSDI applications, 2017-2022

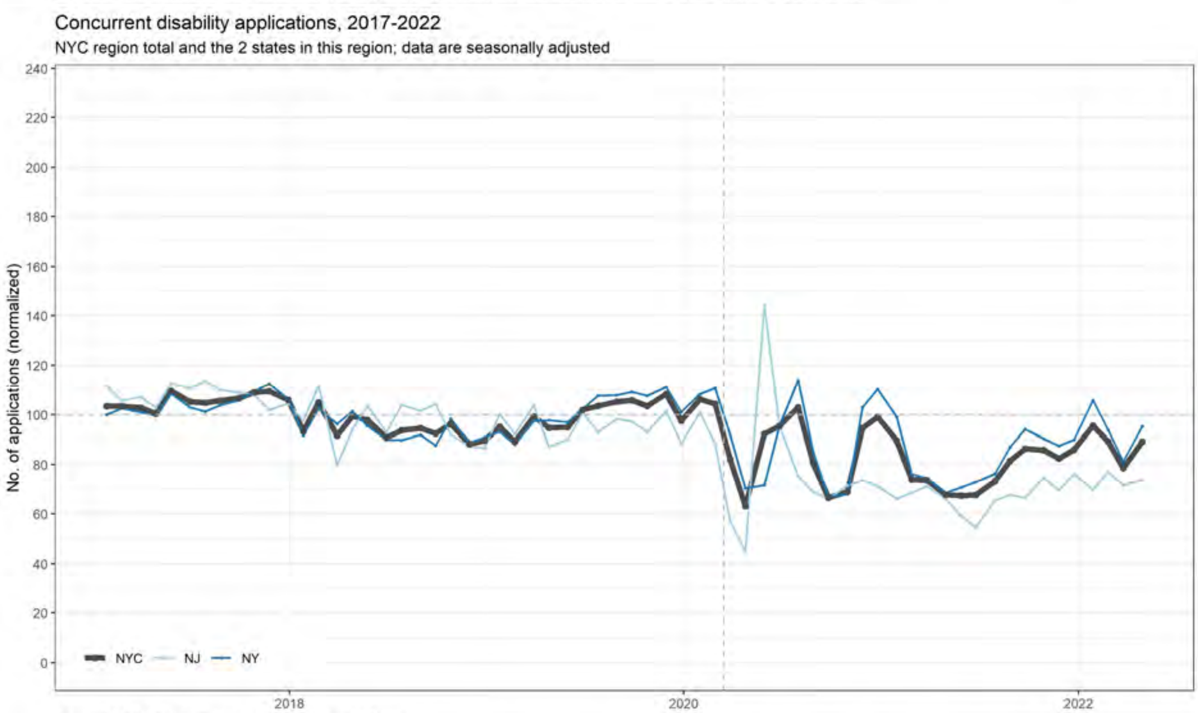
NYC region total and the 2 states in this region; data are seasonally adjusted



Source: SSA State Agency Monthly Workload Data (MOWL).
Note For each state and the region total,
the number of SSDI applications are normalized by setting the average monthly SSDI applications in this state or region from 2017 to 2019 to 100.



Source: SSA State Agency Monthly Workload Data (MOWL).
Note For each state and the region total,
the number of SSI applications are normalized by setting the average monthly SSI applications in this state or region from 2017 to 2019 to 100.



Source: SSA State Agency Monthly Workload Data (MOWL).
Note For each state and the region total,
the number of concurrent applications are normalized by setting the average monthly concurrent applications in this state or region from 2017 to 2019 to 100.

Among NYC-area states, SSDI, SSI, and concurrent applications decrease at the start of the pandemic and then peak in the first half of 2020. In contrast to New Jersey, which has remained stable since then, New York State reaches another peak in late 2020 and then becomes stable, coinciding with a surge in COVID cases in New York State.

h) PHL (Philadelphia) region

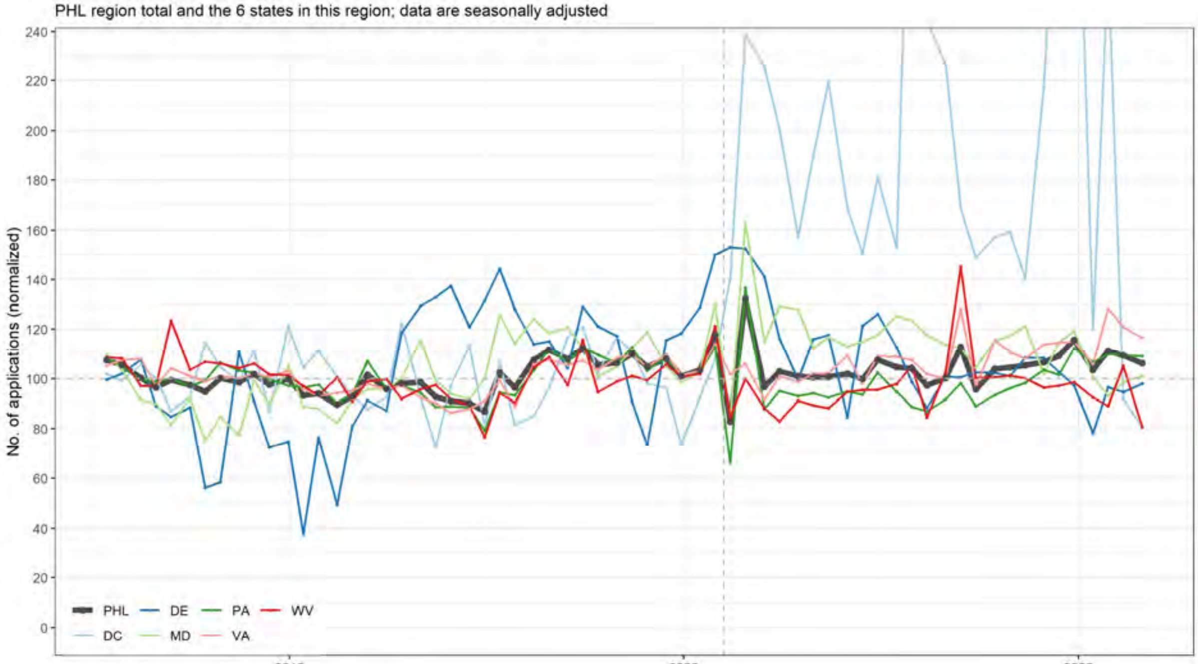
Total social security disability applications, 2017-2022

PHL region total and the 6 states in this region; data are seasonally adjusted

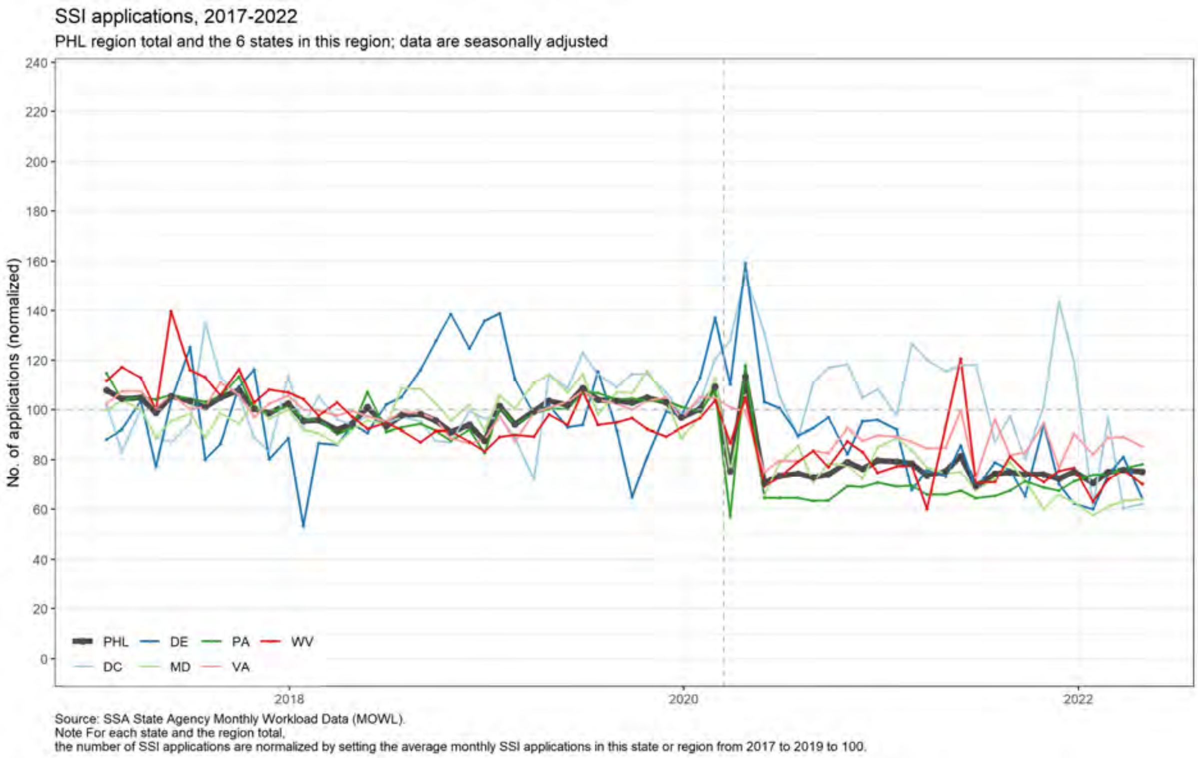
Source: SSA State Agency Monthly Workload Data (MOWL).
Note For each state and the region total,
the number of all applications (SSDI + SSI + concurrent) are normalized by setting the average monthly all applications in this state or region from 2017 to 2019 to 100.

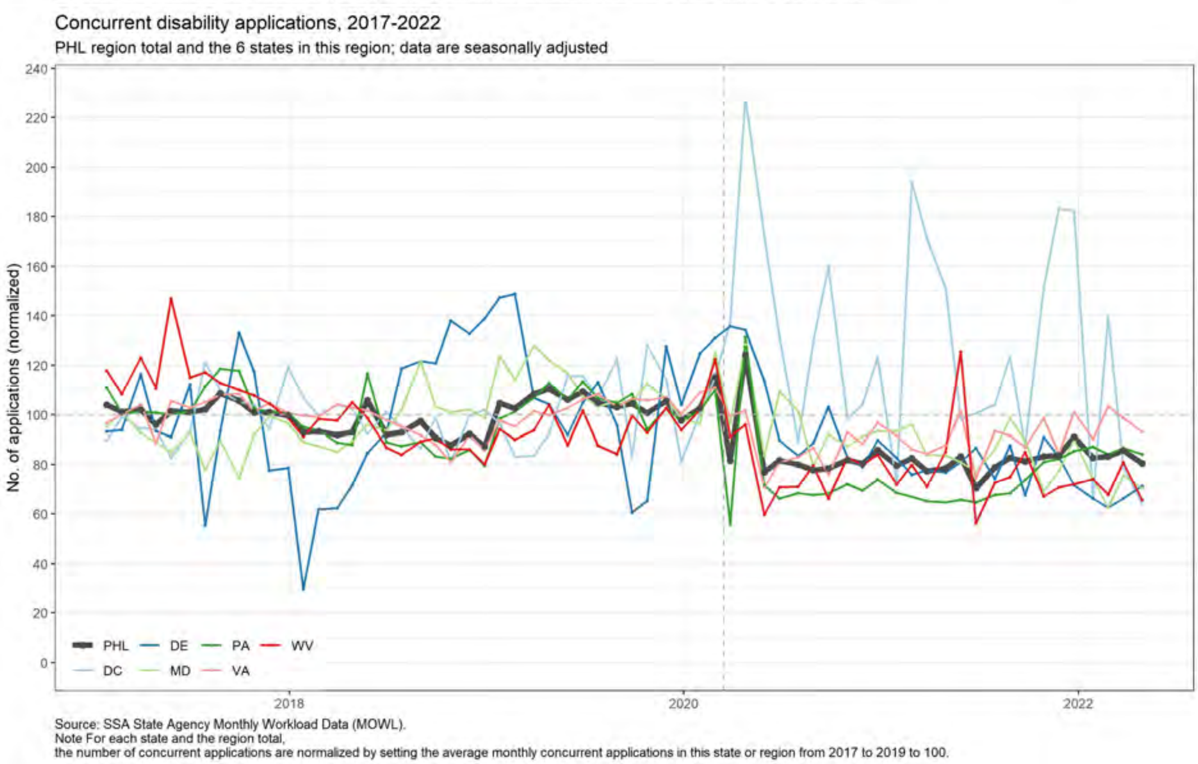
SSDI applications, 2017-2022

PHL region total and the 6 states in this region; data are seasonally adjusted



Source: SSA State Agency Monthly Workload Data (MOWL).
Note For each state and the region total,
the number of SSDI applications are normalized by setting the average monthly SSDI applications in this state or region from 2017 to 2019 to 100.



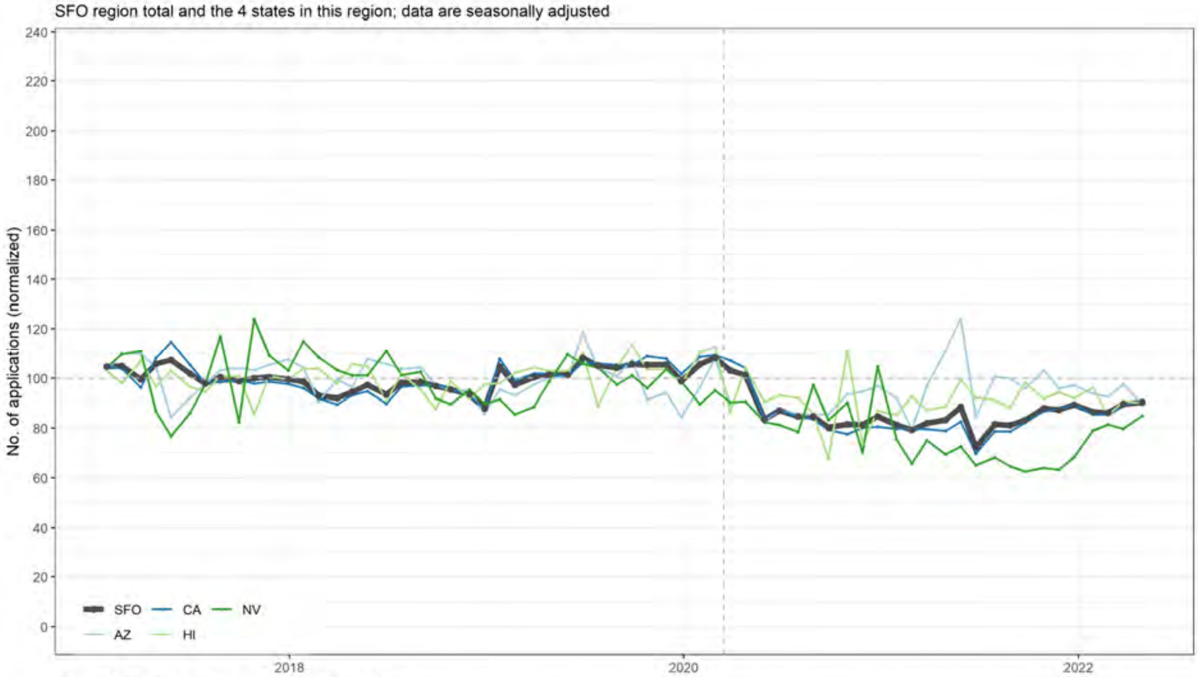


Since March 2020, all states in the PHL region, except Washington, DC, have had steady SSDI, SSI, and concurrent applications. Applications in Washington, DC fluctuate significantly, peaking in early 2020, 2021 and 2022, and late 2021.

i) SFO (San Francisco) region

Total social security disability applications, 2017-2022

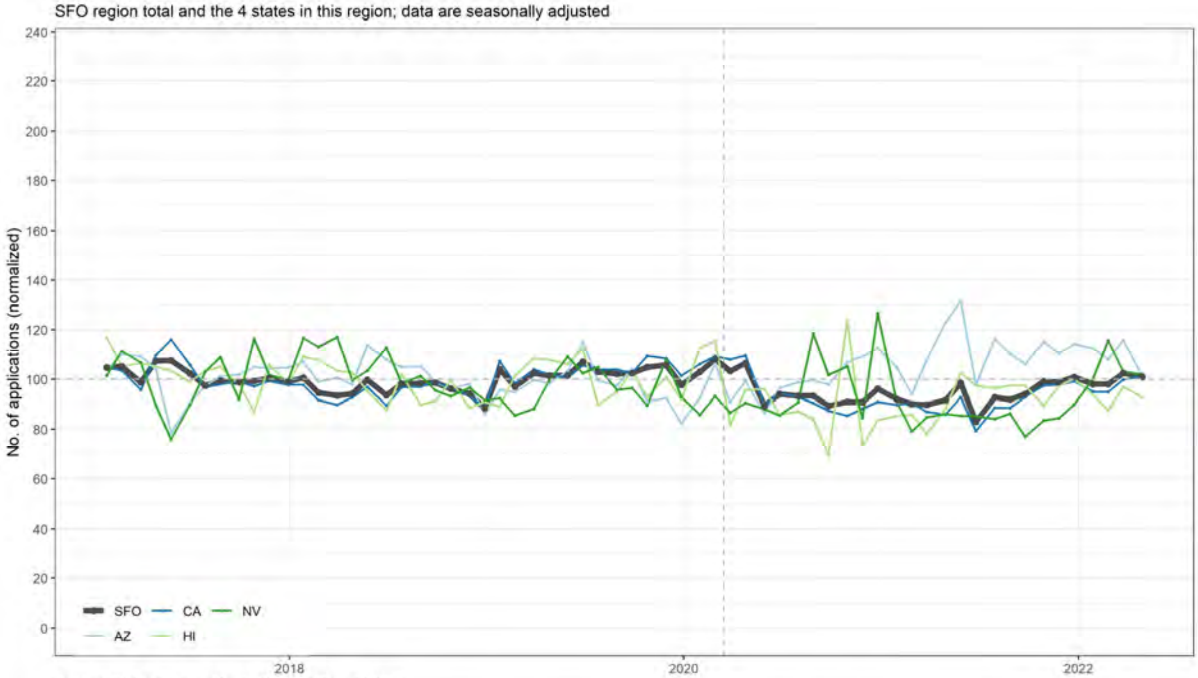
SFO region total and the 4 states in this region; data are seasonally adjusted



Source: SSA State Agency Monthly Workload Data (MOWL).
Note For each state and the region total,
the number of all applications (SSDI + SSI + concurrent) are normalized by setting the average monthly all applications in this state or region from 2017 to 2019 to 100.

SSDI applications, 2017-2022

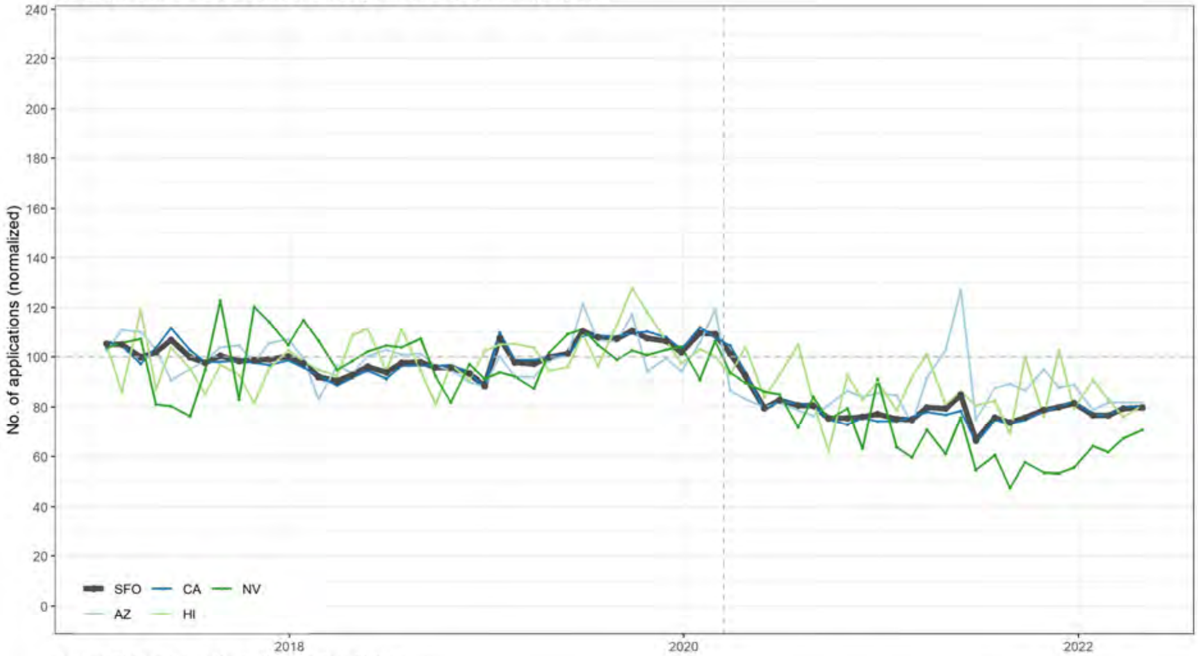
SFO region total and the 4 states in this region; data are seasonally adjusted



Source: SSA State Agency Monthly Workload Data (MOWL).
Note For each state and the region total,
the number of SSDI applications are normalized by setting the average monthly SSDI applications in this state or region from 2017 to 2019 to 100.

SSI applications, 2017-2022

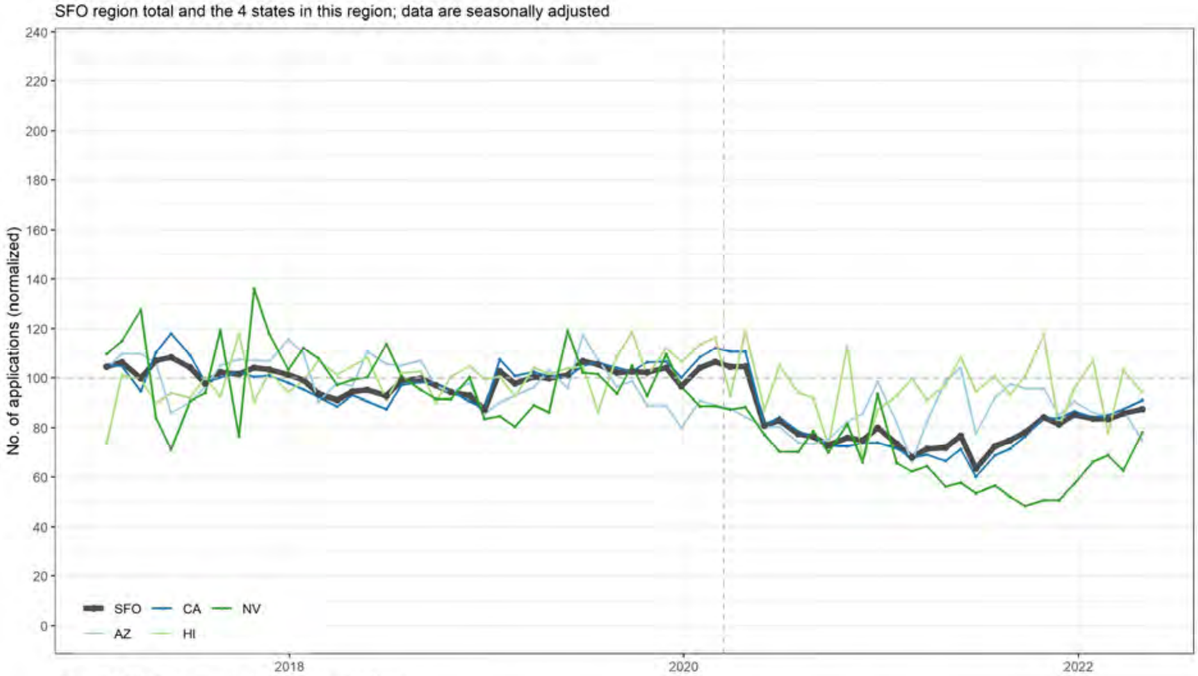
SFO region total and the 4 states in this region; data are seasonally adjusted



Source: SSA State Agency Monthly Workload Data (MOWL).
Note For each state and the region total,
the number of SSI applications are normalized by setting the average monthly SSI applications in this state or region from 2017 to 2019 to 100.

Concurrent disability applications, 2017-2022

SFO region total and the 4 states in this region; data are seasonally adjusted



Source: SSA State Agency Monthly Workload Data (MOWL).
Note For each state and the region total,
the number of concurrent applications are normalized by setting the average monthly concurrent applications in this state or region from 2017 to 2019 to 100.

Among the states in the SFO region, SSDI, SSI, and concurrent applications show small fluctuations during the pandemic, like those seen before the pandemic. In more detail, SSI and concurrent applications show a slight downward trend and SSDI applications show a slight upward trend.

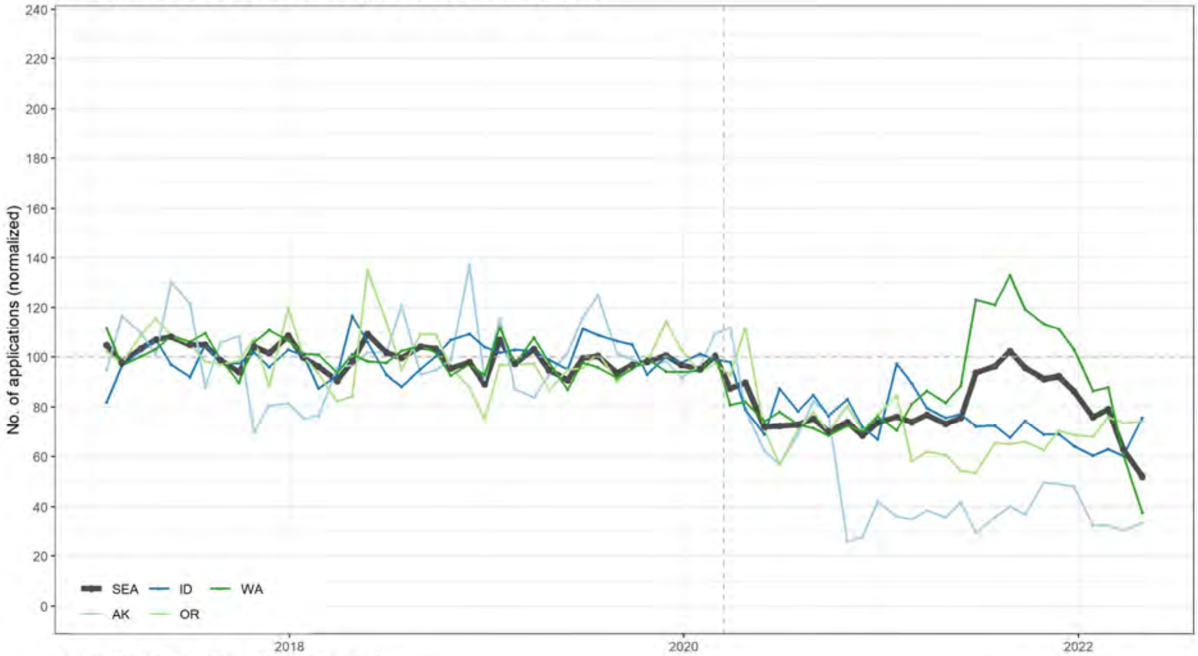
j) SEA (Seattle) region

Source: SSA State Agency Monthly Workload Data (MOWL).
Note For each state and the region total,
the number of all applications (SSDI + SSI + concurrent) are normalized by setting the average monthly all applications in this state or region from 2017 to 2019 to 100.

Source: SSA State Agency Monthly Workload Data (MOWL).
Note For each state and the region total,
the number of SSDI applications are normalized by setting the average monthly SSDI applications in this state or region from 2017 to 2019 to 100.

SSI applications, 2017-2022

SEA region total and the 4 states in this region; data are seasonally adjusted



Source: SSA State Agency Monthly Workload Data (MOWL).
Note For each state and the region total,
the number of SSI applications are normalized by setting the average monthly SSI applications in this state or region from 2017 to 2019 to 100.

Concurrent disability applications, 2017-2022

SEA region total and the 4 states in this region; data are seasonally adjusted

Source: SSA State Agency Monthly Workload Data (MOWL).
Note For each state and the region total,
the number of concurrent applications are normalized by setting the average monthly concurrent applications in this state or region from 2017 to 2019 to 100.

Since March 2020, all states in the SEA region have had a steady stream of concurrent applications. In addition, SSDI and SSI applications peak in the second half of 2021 and then decline.

Appendix C: Methods and results for event study and DD models

Methods used for DD and event studies:

1. <u>The June withdrawal pandemic UI equation</u> (Time period from 2016.01-2022.04)

$$y_{st} = \alpha + \sum_{k=-3,k\neq-1}^{3} \beta_t(I_{t=k} * Withdraw_i) + \alpha_1 * Unemply\_rate_{st} + \gamma_s + \delta_y + \epsilon_{st}$$

y_{st} : a set of variables {SSDI seasonally-adjusted applications, SSI seasonally-adjusted applications, concurrent seasonally-adjusted applications, all seasonally-adjusted applications, normalized SSDI seasonally-adjusted applications}, s indicates state and t indicates month.

I_t: an indicator for an event study.

$Withdraw_i$: a dummy variable and equals one when the state ended the pandemic UI program in June 2021. There are 22 states terminated in June, 4 states terminated in July (dropped), and 25 states terminated in September.

γ_s: state fixed effect.

δ_y: we consider year dummies are from 2016 to 2020, since the early withdraw event period is from March 2021.3 to September 2021.

$Unemply\_rate_{st}$: seasonally adjusted unemployment rate.

Standard errors are robust and clustered at the state level.

2. <u>The September withdrawal pandemic UI equation</u> (Time period from 2016.01-2022.04)

$$y_{st} = \alpha + \sum_{k=-2,k\neq-1}^{7} \beta_t * I_{t=k} + \alpha_1 * Unemply\_rate_{st} + \gamma_s + \delta_y + \epsilon_{st}$$

y_{st} : a set of variables {SSDI seasonally-adjusted applications, SSI seasonally-adjusted applications, concurrent seasonally-adjusted applications, all seasonally-adjusted applications}, s indicates state and t indicates month.

I_t: an indicator for an event study.

γ_s: state fixed effect.

δ_y: we consider year dummies are from 2016 to 2020, since the withdraw event period is from 2021.7 to 2022.4.

$Unemply\_rate_{st}$: seasonally adjusted unemployment rate.

Standard errors are robust and clustered at the state level.

3. <u>DD equation for post_covid (2016.01-2022.04)</u>

$$y_{st} = \alpha + \beta_1 * Post\ Covid_t + \gamma * Unemply_{rate_{st}} + \gamma_1 * Post\ Covid_t * Cum_{case_{st}} + \gamma_2 * Post\ Covid_t * Cum_{death_{st}} + \beta_2 * Post\ Covid_t * High_{conne\ \ s} + \beta_3 * Post\ Covid_t * Medicaid_{AC\ \ s} + \beta_4 * Post\ Covid_t * Group1_s + \beta_5 * Post\ Covid_t * Group2_s + \alpha_1 * Post\ Covid_t * Stay\ at\ home_{st} + \alpha_2 * Post\ Covid_t * Emergency_{st} + \alpha_3 * Post\ Covid_t * School\ \ closure_{st} + \alpha_4 * Post\ Covid_t * Restaurant\ closure_{st} + +\gamma_s + \delta_y + \epsilon_{st}$$

y_{st} : a set of variables {SSDI seasonally-adjusted applications, SSI seasonally-adjusted applications, concurrent seasonally-adjusted applications}.

$Post\ Covid_t$: an indicator for post Covid-19 period from March 2020 to April 2022

$High\_connect_s$ is considered as one if the states whose broadband internet service are greater than the median level of broadband internet service and this information is from American Community Survey in 2020.

$Medicaid\_ACA_s$ is 1 for those states under Medicaid expansion during this time period.

Group 1 include states AK, ID, KS, NE, NV, OR, UT that have the same Medicaid eligibility rules as SSI but require a separate application.

Group 2 include states CT, HI, IL, MN, MO, NH, ND, OK, VA that has different applications and eligibility rules for SSI and Medicaid.

$Stay\ at\ home_{st}$, $Emergency_{st}$, $School\ closure_{st}$ and $Restaurant\ closure_{st}$ are dummies, and are one for this COVID policy takes effect on the month t.

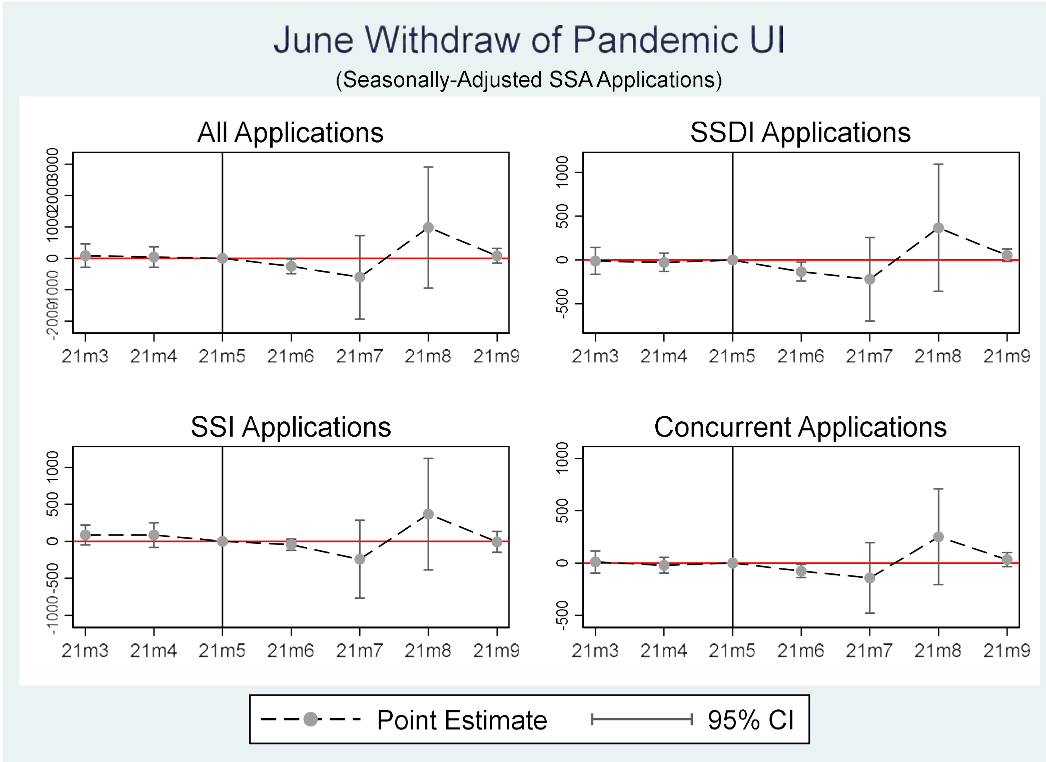
Cum_case_{st}: adjusted cumulative COVID case.

Cum_death_{st}: adjusted cumulative COVID death.

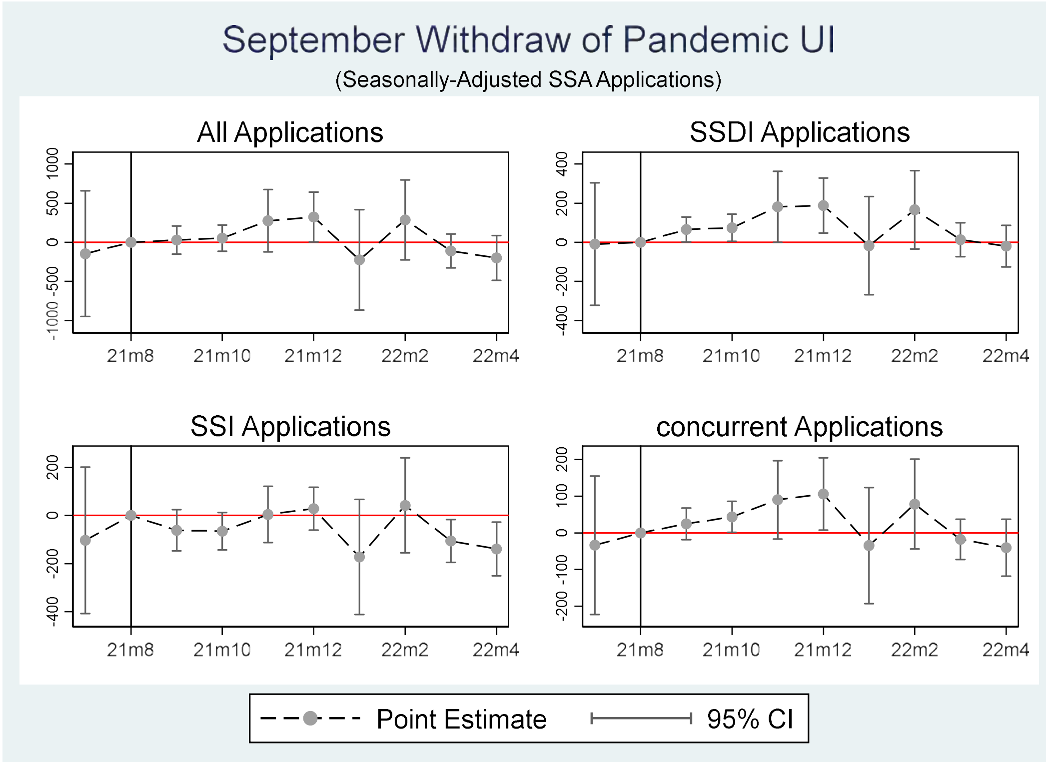
4. <u>Counterfactual analysis (forecast_error, 2020.3-2021.2)</u>

$$y_{st} = \alpha + \beta_1 * Stay\ at\ home_{st} + \beta_2 * Emergency_{st} + \beta_3 * School\ closure_{st} + \beta_4 * Restarant\ closure_{st} + \beta_5 * Unemply\_rate_{st} + \beta_6 * Cum\_case_{st} + \beta_7 * Cum\_death_{st} + \gamma_s + \delta_y + \epsilon_{st}$$

$$y_{st} = \alpha + \beta_1 * Stay\ at\ home_{st} + \beta_2 * Emergency_{st} + \beta_3 * School\ closure_{st} + \beta_4 * Restarant\ closure_{st} + \beta_5 * Unemply\_rate_{st} + \beta_6 * Medicaid\_ACA_s + \beta_7 * High\_connect_s + \beta_8 * Group1_s + \beta_9 * Group2_s + \delta_y + \epsilon_{st}$$



Appendix C Figure 1: Event study – effect of June withdrawal of pandemic UI on disability applications



Appendix C Figure 2: Event study – effect of September withdrawal of pandemic UI on disability applications

Appendix C Table 1. DID results for SSDI applications.

	SSDI	SSDI	SSDI	SSDI	SSDI	SSDI	SSDI	SSDI
Post Covid	-189.747***	-53.508	84.531	-39.034	-60.715*	-56.109	-106.584***	-61.716*
	(45.062)	(41.061)	(86.116)	(38.553)	(30.434)	(67.172)	(29.410)	(31.273)
Unemply_rate	-4.370	-818.646	-313.025	-873.534	-844.613*	-909.792*	-912.909*	-921.448
	(482.355)	(645.214)	(512.037)	(536.820)	(470.652)	(478.315)	(507.656)	(621.076)
Post Covid * Cum_death	0.015							
	(0.012)							
Post Covid * Cum_case	-0.000							
	(0.000)							
Post Covid * High_connect		-25.383						
		(79.658)						
Post Covid * Medicaid_ACA			-245.586**					
			(118.863)					
Post Covid * Group1				-69.018				
				(59.071)				
Post Covid * Group2				-84.777				
				(69.422)				
Post Covid * Stay at home					-16.307			
					(51.054)			
Post Covid * Emergency						-5.741		
						(67.960)		
Post Covid * School closure							46.072	
							(34.230)	
Post Covid * Restaurant closure								1.368
								(49.124)
Constant	294.898***	201.284***	194.620***	224.331***	207.105***	211.044***	211.272***	212.186***
	(61.774)	(55.141)	(39.448)	(41.038)	(35.519)	(35.862)	(39.946)	(47.431)
Observations	1377	3876	3876	3876	3876	3876	3876	3876
Adjusted R^2	0.915	0.960	0.960	0.961	0.960	0.960	0.960	0.960
Year Fixed Effect	Y	Y	Y	Y	Y	Y	Y	Y
State Fixed Effect	Y	Y	Y	Y	Y	Y	Y	Y

Appendix C Table 2. DID results for SSI applications.

	SSI	SSI	SSI	SSI	SSI	SSI	SSI	SSI
Post Covid	-326.101***	-203.333***	-200.230***	-282.011***	-226.378***	-213.987***	-28.036	-238.584***
	(60.497)	(53.967)	(62.887)	(54.041)	(47.196)	(76.524)	(52.828)	(47.833)
Unemply_rate	-578.164	-1784.279*	-1936.796*	-2015.589*	-2220.670**	-2024.527*	-2047.813*	-2563.588*
	(553.788)	(975.658)	(1055.785)	(1020.317)	(1072.320)	(1085.223)	(1118.600)	(1312.629)
Post Covid * Cum_death	-0.002							
	(0.008)							
Post Covid * Cum_case	0.000							
	(0.000)							
Post Covid * High_connect		-65.720						
		(91.057)						
Post Covid * Medicaid_ACA			-40.261					
			(74.812)					
Post Covid * Group1				257.850***				
				(66.745)				
Post Covid * Group2				122.030				
				(96.464)				
Post Covid * Stay at home					42.447			
					(71.097)			
Post Covid * Emergency						-10.736		
						(55.365)		
Post Covid * School closure							-200.708***	
							(51.411)	
Post Covid * Restaurant closure								125.984**
								(53.614)
Constant	451.865***	377.970***	402.374***	335.163***	417.404***	403.781***	407.479***	440.945***
	(78.325)	(76.679)	(90.616)	(77.424)	(88.880)	(89.001)	(93.121)	(105.877)
Observations	1377	3876	3876	3876	3876	3876	3876	3876
Adjusted R^2	0.915	0.960	0.960	0.961	0.960	0.960	0.960	0.960
Year Fixed Effect	Y	Y	Y	Y	Y	Y	Y	Y
State Fixed Effect	Y	Y	Y	Y	Y	Y	Y	Y

Appendix C Table 3. DID results for Concurrent applications.

	Concurrent	Concurrent	Concurrent	Concurrent	Concurrent	Concurrent	Concurrent	Concurrent
Post Covid	-195.214***	-122.494***	-100.054**	-151.233***	-132.974***	-109.594***	-45.558*	-141.937***
	(37.186)	(30.521)	(38.008)	(30.612)	(27.412)	(40.300)	(23.581)	(27.599)
Unemply_rate	-34.412	-837.479*	-796.779	-885.879*	-1247.907**	-895.223*	-921.540*	-1389.209**
	(323.620)	(478.734)	(496.829)	(495.249)	(534.141)	(511.590)	(528.378)	(664.645)
Post Covid * Cum_death	-0.003							
	(0.007)							
Post Covid * Cum_case	0.000*							
	(0.000)							
Post Covid * High_connect		-20.623						
		(45.402)						
Post Covid * Medicaid_ACA			-48.720					
			(44.317)					
Post Covid * Group1				113.294***				
				(37.339)				
Post Covid * Group2				29.858				
				(51.663)				
Post Covid * Stay at home					76.047*			
					(38.269)			
Post Covid * Emergency						-20.478		
						(28.814)		
Post Covid * School closure							-85.420***	
							(22.475)	
Post Covid * Restaurant closure								112.831***
								(36.010)
Constant	262.023***	223.495***	228.629***	198.437***	253.918***	229.349***	233.011***	264.059***
	(47.327)	(37.223)	(41.720)	(37.834)	(42.553)	(40.632)	(42.878)	(52.147)
Observations	1377	3876	3876	3876	3876	3876	3876	3876
Adjusted R^2	0.898	0.951	0.951	0.951	0.951	0.951	0.951	0.951
Year Fixed Effect	Y	Y	Y	Y	Y	Y	Y	Y
State Fixed Effect	Y	Y	Y	Y	Y	Y	Y	Y