Disparities in Access to Unemployment Insurance During the COVID-19 Pandemic: Lessons from U.S. and California Claims Data

ALEX BELL, THOMAS J. HEDIN, PETER MANNINO, ROOZBEH MOGHADAM,
GEOFFREY SCHNORR and TILL VON WACHTER

NOVEMBER 2021

CALIFORNIA POLICY LAB

Department of Labor Summer Data Challenge Report

Disparities in Access to Unemployment Insurance During the COVID-19 Pandemic: Lessons from U.S. and California Claims Data

Alex Bell, Thomas J. Hedin, Peter Mannino, Roozbeh Moghadam, Geoffrey Schnorr and Till von Wachter[1]

Executive Summary

Unemployment Insurance (UI) benefits provided a lifeline to workers who lost their jobs during the pandemic. However, access to these benefits has been uneven across communities and states (Edwards, 2020). Identifying and documenting these disparities is an important step to addressing them and to rendering the UI system more equitable. Utilizing a conceptual framework of unemployment claims, we developed three metrics to measure access to UI benefits across the claim lifecycle. We then analyzed these measures to provide insight into differential access to UI benefits across U.S. states and across counties within California.

The first measure of access is the First Payment Rate and corresponds to the earliest part of the claim lifecycle. It measures the share of people who file their first claim and who subsequently receive a UI payment. After the First Payment Rate, the primary measure of access in the report is the Recipiency Rate. The recipiency rate measures the share of unemployed or underemployed workers who are actually receiving UI benefits. This is the traditional measure (Wittenberg et al., 1999) of UI access, and reflects access in the middle of the claim lifecycle. The final measure of access is the Exhaustion Rate, which corresponds to the final part of the claim lifecycle. It measures the share of claimants who have exhausted eligibility for both regular and extended UI benefits.

We calculated these metrics in each state by using publicly available data from the U.S. Department of Labor reports and by county in California using tabulations based on individual-level claims data from the California Employment Development Department. The additional information available in the California claims data allows us to improve and further segment our measures of access, allowing us to identify new facts and patterns from the data. We generated these metrics for the year 2020 and focused our analysis from the beginning of the pandemic in March through December 2020, just prior to the initial rollout of COVID-19 vaccines. In addition, we compared these to the corresponding values in December 2019 as a pre-pandemic benchmark.

We use these measures to analyze disparities in access to UI benefits during and before the pandemic and identify community attributes and policy choices that are associated with

---

[1] This report was prepared for the U.S. Department of Labor (DOL), Chief Evaluation Office (CEO) by the authors. The views expressed are those of the authors and should not be attributed to DOL, nor does mention of trade names, commercial products, or organizations imply endorsement of same by the U.S. Government.

differential access. This analysis cannot identify causal relationships, however, across metrics, there is a pattern of correlations showing that workers in states with more generous labor and UI policies have greater access to benefits, potentially indicating the importance of policy choices in shaping UI access. The correlations also show a pattern by which less affluent areas and areas with a higher share of disadvantaged social groups are associated with lower access to UI benefits. Additional research is needed to identify the causal mechanisms between policies and UI access.

Along with research on the effects of rules of the UI and other state and federal programs, we conclude the report by providing further recommendations on future data collection and research funding priorities.

Key Research Findings

In what follows, unless stated otherwise, findings from the analysis for the pandemic refer to December 2020, and findings from the analysis for pre-pandemic refers to December 2019.

- Recipiency Rates
    - About 60% of unemployed Americans collected UI benefits during December 2020, up from 16% of the unemployed in December of 2019. This rate varied dramatically across U.S. states but less so across counties in California.
    - Across states, the range between the bottom 25% and the top 75% states—also called the inter-quartile range (IQR)—was 41% to 71%. If all states had the recipiency rate of New York, a high recipiency state, then six million more people would have received benefits in December 2020.
    - Within California, where all the UI policy parameters are constant across counties, the recipiency rate is above the U.S. average, and there is substantially less variation across counties with an IQR of 78% to 86%.
    - Recipiency rates were higher in states with more generous UI programs (as measured by attributes such as the potential duration, and maximum benefit levels). Recipiency rates were lower in states with more Black residents and in states with lower average incomes.
    - Across California, recipiency rates during the pandemic were higher in more affluent counties and those with more access to broadband. Recipiency rates were lower in counties with more residents of limited English-speaking proficiency, as well as those counties with more Black or Hispanic residents.
- First Payment Rates
    - Nationally, about 70% of new initial claims filed near the start of the pandemic were paid. However, substantial heterogeneity exists across states.
    - Payment rates were higher in states with alternative base period eligibility, as well as states that are more affluent. States with more Black workers paid lower shares of claims.

    - For California, using longitudinal UI histories we can calculate payment rates of first claims that are more precise than possible based on analyses using publicly available data.
    - Within California, more claims were paid near the start of the pandemic in counties that were more affluent, had a lower share of Hispanic workers, and more access to high-speed broadband internet.
- Exhaustion Rates
    - Nationally, about 6% of jobless workers claiming UI had exhausted their benefits during the first week of December 2020. In some states, this was as high as 24%.
    - Exhaustions as a share of claimants declined to 1% at the beginning of the pandemic in March as millions of unemployed workers entered the UI system as claimants, and gradually increased through December.
    - States with longer potential UI durations and mandatory sick leave or paid family leave programs saw lower exhaustion rates during the pandemic. A higher share of claimants also exhausted in states with more Black residents.
    - Within California, counties with more limited-English speakers and higher rates of COVID-19 cases saw higher rates of exhaustion, as did those with higher shares of Black and Hispanic residents.
    - In California, individual-level claims data allow us to calculate the rate of exhaustion among a cohort of UI claimants entering in a given month, which more accurately captures the generosity of UI benefits than the standard measure. This measure tends to be higher than the typical measure based on public data which captures exhaustions among all claimants at a given date.
- Conclusion
    - Given these initial results on disparities in access to UI during the pandemic, we recommend that the scope of the analysis should be expanded to include more current weeks of data, and suggest several ways for improving data collection.
    - We conclude with several additional ways that DOL might fund follow-on research in this vein.

Overall, the report highlights important disparities in access to UI benefits in the U.S. On all three measures, reduced access to benefits is correlated with lower socioeconomic status or the presence of disadvantaged social groups. If lower performing states could improve their access to UI to the level of high performing states, then millions of additional people would gain access to vital benefits as they struggle with unemployment. The existing disparities in access to benefits also mean that reforms that improved access could have a particularly strong impact on disadvantaged populations.

Comparing California with the U.S. as a whole, California's UI system performed very well. California had the fourth-highest recipiency rate in the U.S. and was above the U.S. average on the two other measures of access. The report also shows that disparities in access, when they exist, exist across the U.S. and are not unique to California. They also often pertain to aspects of the UI program that are set at the federal level or arise from inequalities in the wider labor market outside of the reach of the UI system. The light that this report shines on variation in access to UI benefits can help build support for addressing those differences, which would benefit Californians and unemployed people across the U.S. as a whole.

Table of Contents

1. Introduction

1.1 Defining Access to Unemployment Insurance

The unprecedented surge in job losses and Unemployment Insurance (UI) claims during the COVID-19 pandemic, and the surge in unemployment among lower-wage workers from sectors directly affected by the pandemic, refocused long-standing concerns about equity and access to the UI system.[2]

This report documents key patterns of community-level disparities in access to UI during the pandemic. To operationalize our notion of access to UI, we rely on a comprehensive conceptual framework that allows us to track a jobless worker's access to UI benefits across three discrete stages in the lifecycle of a potential UI claim. To document the degrees of disparities in access throughout the lifecycle of a UI claim, the analysis develops and compares measures for each stage of access both across states and at more local levels within California. We then correlate these measures of access with state and county characteristics to measure differences in access across these attributes.

We utilize public data from U.S. Department of Labor Employment and Training Administration (DOL ETA) and the Current Population Survey (CPS) as well as our team's unique access to California's UI claims micro data, made accessible through a partnership with the state's Employment Development Department. We combine these data with detailed state-level demographic, labor market, and public health characteristics across states for the entire U.S. and at the county level in California. We also collected information on state-level differences in the UI programs and states' tax and benefit systems. State UI programs differ on attributes such as their maximum Potential Benefit Durations (PBD), their Weekly Benefit Amounts (WBA), and whether they allow Alternate Base Periods (ABP) to determine program eligibility. For example, state PBDs ranged from 30 weeks in Massachusetts to 12 weeks in North Carolina and Florida, maximum WBAs ranged from over $840 in Washington to only $235 in Mississippi, and 38 states offered ABPs for determining UI eligibility.

Conceptual Framework

To study access to UI, this paper relies on the following integrated conceptual model for measuring community-level access to UI. Figure 1 provides a high-level overview of our data-driven framework.

Our framework begins at the point at which a jobless worker files a new initial claim, which for many jobless workers will be their first interaction with the UI system. Reasons for a claim to be rejected can be either monetary (e.g., insufficient prior earnings) or non-monetary (e.g., claimant quit their job without good cause). Once a new initial claim has been filed, we define the first positive measure of access by whether a first payment is issued for the claim.[3] Although for the

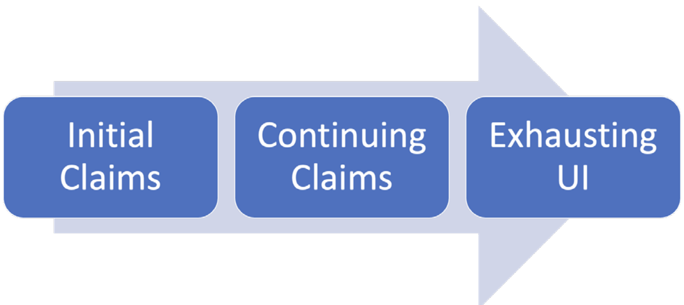
---

[2] See, for instance, January 21, 2021, Executive Order On Advancing Racial Equity and Support for Underserved Communities Through the Federal Government.

[3] Although the focus of this report is *whether* claims are paid, important questions have arisen during the pandemic concerning the *timeliness* of payments. For information on this dimension, see The Century Foundation's Dashboard: https://tcf.org/content/data/unemployment-insurance-data-dashboard.

limited scope of this report we refer to the share of claims paid as a measure of access, this measure can be further refined by removing from the denominator any claimants whose claim was not paid because the claimant found alternative work. (We return to possible extensions to the methodology in Section 3.)

Figure 1: Measuring Access in UI Claims Data



Whereas our earliest indicator of access pertains only to people who have applied for UI benefits, our main measure of access is a point-in-time measure among all unemployed people: the recipiency rate. For this report, we focus only on measuring the recipiency rate of regular UI, not including Pandemic Unemployment Assistance (PUA), one of the federal supplemental programs added in response to the crisis. We define the recipiency rate to be the share of unemployed (or under-employed) workers in a given week who were collecting *regular UI* benefits. We hypothesize that this measure will be lower whenever a jobless worker:

1. Did not apply for benefits.
2. Applied for benefits but did not receive them.
3. Applied for and received benefits, but exhausted all of their benefits.
4. Applied for and received benefits, but stopped receiving benefits for other reasons, including failure of the claimant to recertify or a change in the claimant's eligibility status.

In this report, we do not attempt to measure the first mechanism.[4] The second mechanism corresponds to our earliest measure of access, the share of claims paid. The end-stage exhaustion rate alluded to in the third mechanism is our final measure of access.

Exhaustion rates are a useful measure of access because, to a large degree, they reflect how fully insured workers were against the length of job loss they experienced (Schmieder et al., 2012). Still, like first payment rates, exhaustion rates could also diverge from a more ideal measure of access if claimants who exhaust also find suitable work in the week of exhaustion or for other reasons related to moral hazard. Future work should examine the reemployment prospects of workers who exhausted benefits during the pandemic.

Scope of Analysis

The scope of this report is to establish basic descriptive facts on the above three measures of access. Our analysis is primarily cross-sectional, in that we show how the measures differ

[4] Future work could relate the number of new initial claims to data on separations from JOLTS, though that analysis will be somewhat limited in terms of what can be observed about workers.

across space. Although time-series analysis is not the present focus, this report also sheds light on how these measures differed from their pre-pandemic baselines.

The outline for the remainder of this report is as follows. Section 1.2 describes our methodological approach in greater detail and Section 1.3 presents descriptive statistics. Sections 2.1, 2.2, and 2.3 present the results of our analysis of access to UI when applied to rates of recipiency, first payments, and exhaustions, respectively. Section 3 concludes with a discussion of additional areas for research.

1.2 Operationalizing the Measures of Access

The data for this report stems from the Department of Labor (DOL) and Employment Development Department (EDD).

Data from the DOL was taken from its Office of Unemployment Insurance through the publicly available "Data Downloads" portal on the office's website, which is updated daily. The data extracted from this portal dates back to the year 1984, and it contains state-level employment information for all 50 states. The variables in these extracted datasets are reported on either a weekly or monthly basis. For much of our analysis, we combine or divide various variables within the DOL data, such as our measure of new initial claims that are paid, which divides the variable for new payments by the variable for new initial claims.

For our within-California analysis, we use administrative data from EDD on initial and continuing claims. The initial claims data include micro-level data on all claims filed in the state of California. The initial claim dataset has information on the date of filing the claim, the beginning of the benefit year, the maximum benefit amount, and demographics. In this paper, we use new initial claims to estimate the first payment rates in Section 2.

Another source of data from EDD is continuing claims data which includes payments information for continuing claimants. An important feature of this data is that we can count continuing claimants by the week of unemployment, which is the week for which they receive their payment, rather than the week that the payment is processed, which is how data are reported by DOL. This is specifically important for measuring the recipiency rate in Section 1 because the unemployment numbers are based on the week of unemployment, and counting continuing claims based on the week of unemployment improves the accuracy of the results compared to public data (Bell et al., 2020). Another feature of this data is having information on the last payment. We observe the last payment of each claim for all available programs, allowing us to measure exhaustion rates in Section 3.

Table 1 describes at a high level how each of the three measures of access are operationalized in the DOL and EDD datasets. Below, we discuss each measure in greater detail.

Table 1: Definitions of Key Access Measures, EDD and DOL

Access Measure	Definition in Employment Development Department Micro-data	Definition in State Department of Labor Aggregates

Initial Claims Payment Rate	Number of regular UI paid claimants divided by regular claimants at quarterly level. Drop anyone who filed a PUA claim in that quarter from the sample.	First Payments for regular UI divided by new regular initial claims, at the monthly level.
Recipiency Rate	Number of claimants who claimed regular UI benefits for unemployment experienced in a given week divided by our U6 estimate.	Number of weeks paid across regular UI programs divided by number of (U6) unemployed people in CPS.
Exhaustion Rate	Number of exhausted claimants divided by number of people who claimed UI for unemployment in a given week. First, we exclude claimants who have received only PUA payments in the time period of analysis. We code exhaustions when a claimant receives a final payment for a program and does not receive another payment for any UI program for 4 weeks. For the case of claimants who receive regular and then PUA payments, transitions that occur within 4 weeks are not coded as exhaustions.	The denominator for exhaustions is calculated by summing the number of people paid in a week for regular UI, including extensions. The numerator is equal to the number of final payments for the final extension in a given time period. During periods when there are no extension programs, the numerator is final payments for state UI.

Measurement of Recipiency Rates

We measure the UI recipiency rate as the number of people collecting regular UI benefits divided by the number of unemployed workers in an area. In the EDD data, the number of people collecting benefits in a week is defined as the number of people who were paid for unemployment experienced in a given week, regardless of when the benefits were paid. This definition more accurately represents the number of unemployed people receiving UI benefits in a given week, and is the natural counterpart to the number of unemployed people as measured in survey data. In contrast, in the DOL data, the number of people collecting benefits in a week corresponds to the number of payments that were issued that week for regular state UI, Pandemic Emergency Unemployment Compensation (PEUC), or Extended Benefits (EB).[5] Discrepancies can arise when a large number of individuals file and get paid for multiple weeks retroactively. During the crisis, this led to large discrepancies between the two measures, but prior to the crisis, the number of payments issued in a given week was on average similar to the number of individuals receiving payments for unemployment in a given week. In our series of policy briefs, we contrast the two measures further (Bell et al., 2020).

Our denominator — an estimate of the number of people who experienced unemployment in a week — is derived from CPS. At the state level, unemployment is derived from CPS microdata,

[5] Georgia and Florida did not report any PEUC claims during 2020.

and is typically referred to as the U-6 measure, which is broader than the typical number of unemployed published by the U.S. Bureau of Labor Statistics (BLS). As discussed in our series of unemployment policy briefs (Bell et al., 2020), we use this broader measure to account for the fact that workers working part-time involuntarily can receive UI benefits, and that during the crisis, individuals available for work but not actively searching for a job could receive UI benefits.[6] Our numerator excludes claimants receiving PUA benefits, not only to aid comparisons prior to the pandemic and to reduce complications related to reports of fraudulent PUA claims, but also because some PUA claimants may be working reduced hours for *non-economic* reasons, and thus would not be included in the denominator.[7] Furthermore, many business owners would be counted as *employed* if they worked just a single hour during the CPS reference week, but would still be eligible to receive PUA benefits if their business was affected by the pandemic.[8] By focusing just on claimants receiving *regular* UI benefits, we are able to form a more "apples-to-apples" comparison. To construct our denominator at the sub-state (county) level, we base our estimates of the number of unemployed people off Local Area Unemployment Statistics (LAU.S.) estimates, adjusted to mirror U-6.

Measurement of First Payment Rates

Whereas our analysis of recipiency rates during the pandemic focused on December of 2020, when analyzing first payment rates we focus on claimants during the first half of 2020. This timing better aligns with when the pandemic-driven surge of new initial claims began and peaked (Bell et al., 2021).

In general, one can divide initial claims into two main categories: new initial claims and additional claims. New initial claims correspond to "an application for the establishment of a benefit year," and an unemployed person who wants to collect UI benefits must file a new initial claim.[9] Additional claims correspond to claimants who experience an interruption in their benefit certification for one or more weeks due to being employed. Claimants still must be within their

---

[6] According to the definition of the U.S. Bureau of Labor Statistics, the U-6 measure of unemployment includes workers who fall under the traditional measure of unemployed (U-3), along with those working part time for economic reasons and with those marginally attached to the labor force. We supplement the U-6 measure to include workers the BLS believes may have been misclassified as employed despite not being at work during the reference week for reasons related to the pandemic (These workers instead should have been classified as "Unemployed on temporary layoff"). We follow the methodology outlined in Question 5 of the December Employment Situation FAQ to adjust our unemployment estimate for these misclassifications https://www.bls.gov/covid19/employment-situation-covid19-faq-december-2020.htm#ques5. In the text, when we refer to using U-6, we are referencing this adjusted version (called U-6*) which includes these misclassified workers. The BLS does not publish a monthly estimate of U-6 at the state level, so the study team generated a measure of U-6 for California based on the CPS micro data following the definition of the national U-6 measure. Although we use U-6 exclusively for the main analysis, we also calculate state Recipiency Rates using U-3 unemployment and present the figures in the Appendix. Results using either measure are typically similar and comparisons will be highlighted in the footnotes throughout the Recipiency Rate chapter.

[7] https://www.bls.gov/cps/definitions.htm#pter

[8] See California's PUA eligibility criteria here: https://edd.ca.gov/about_edd/coronavirus-2019/pandemic-unemployment-assistance.htm. See the CPS definition here: https://www.bls.gov/cps/definitions.htm#employed.

[9] https://www.edd.ca.gov/uibdg/Miscellaneous_MI_5.htm

benefit year and have remaining benefits in order to file an additional claim. Since additional claims only represent re-entries to UI, we exclude them from our analysis, and only focus on new initial claims.

Two key caveats of this analysis when applied to the DOL data are worth emphasizing, both of which can be remedied with microdata when the analysis focuses on California.

First, in the DOL data, there are substantial payment timing issues. We are only able to look at each state's number of first payments issued in a given month relative to the number of new initial claims filed *in that* month. To the extent that not all first payments are paid in the month in which the claim was filed, we expect this measure to be relatively noisy at the state level, and this would be a particular problem near the start of the pandemic when long payment lags were common.

Second, there are likely cases during the pandemic in which a claim does not result in a first payment under the regular UI program, but the claimant is later able to receive payment under the PUA program. In the DOL data, we are unable to account for these cases as we cannot observe whether the same person applied for or was paid under multiple programs. In the individual-level analysis from EDD, we exclude anyone who ever filed a PUA claim so as to make this measure comparable across time, given that the PUA program did not exist prior to the pandemic. An important avenue for future work, which is beyond the scope of this initial report, will be to document the role the PUA program played in expanding access to UI.

Measurement of Exhaustion Rates

Exhaustion rates have proven particularly difficult to measure, especially in the DOL data. Whereas the term "exhaustion" has at times been used to refer to claimants who exhausted their (regular non-extension) state UI benefits and moved on to extension programs, in this report we aim to define exhaustions as those cases in which a claimant has exhausted state UI *and* all available extensions (including PEUC and EB), which is a more meaningful measure of access given policy changes during the pandemic.

The numerator of our exhaustion rate is an estimate of the number of claimants in a week who exhausted the final week of (regular) UI benefits available to them. During periods when there are no extensions available, the number of people exhausting is the number of final payments issued for the regular UI program.

During periods when extensions are available, we follow different strategies in the two datasets to count exhaustions. In the DOL data, we infer exhaustions based on the number of final payments made under the program that was the last extension program available to most claimants at the time. For instance, since claimants in California were eligible for Extended Benefits during most of the pandemic, we infer the number of exhaustions based on the number of final payments for EB processed that week.[10] In the EDD data, we improve on this measure by counting exhaustions as the co-occurrence of two separate events. The first event is that a

[10] This is a less-than-ideal approximation, as not all claimants are eligible for EB. For instance, our earlier work found that approximately 7% of those claimants who would have exhausted regular UI benefits in December of 2020 had PEUC not been extended then would have not been eligible for EB.

final payment flag was set for a particular UI program, and the second is that another payment does not follow within four weeks.[11] Similar to the other access measurements in this analysis, we only study regular (non-PUA) claimants. However, in the EDD data, in cases where claimants receive their last regular payment and then transit to PUA within four weeks, we do not count them as exhausted because they are still receiving payments – just under a different program. The number of such cases is small with only 384 claimants transitioning in the highest single week.

In either dataset, counts of exhaustions should be handled with caution. As pandemic-era extensions have temporarily lapsed and re-started, it is possible that some claimants may be coded as having exhausted but have in reality been eligible to resume collecting payments after new policies came into effect. Furthermore, even if a claimant exhausts all of their benefits available under one benefit year, if their earnings were high enough, they may be able to establish a new claim. Moreover, the data for exhaustion analysis is up to June 2021. Changes in extension programs afterwards, such as states voluntarily withdrawing from the extension programs or the programs expiring, will likely affect our estimates.

Whereas the numerator of our exhaustion rate in either dataset derives from the issuance of final payments, a question remains about what an appropriate at-risk group should serve as the denominator. In the DOL data, we use the number of continuing claimants as a denominator with which to construct an exhaustion rate. This choice of denominator is chosen largely for convenience. The aggregated nature of the DOL data makes it nearly impossible to relate the number of claimants who exhaust in a given week to any other group that is plausibly at risk of exhausting.

In the EDD microdata, we are able to construct two separate measures of exhaustion. In addition to relating the number of individuals exhausting benefits in a given week to the total number of individuals receiving benefits in that week (to compare with DOL results), we are also able to see specifically what share of claimants who established benefit years in a given week have eventually exhausted benefits. We call this measure the cohort exhaustion rate. In calculating the cohort exhaustion rate, we count all exhausted claimants within a cohort and report that number by date of the established benefit year. But in the other measure, we report the number of exhausted claimants (regardless of their cohort) by the week they experienced exhaustion.

1.3 Descriptive Statistics on Measures of Access

Comparison of DOL and EDD Measures

Table 2 presents descriptive statistics on our three access measures from the EDD and DOL datasets for California. We present means of each measure before and during the pandemic, in the first week of December 2019 and 2020. Since the structure of data in DOL and EDD are

---

[11] In the EDD data, both the final payment flag and gap weeks in payment are based on the week of unemployment.

different, we did not expect to observe identical estimates, but the estimates are in general reasonably close.

Table 2: Comparisons of Key Access Measures, EDD and DOL

Measure	Period	Department of Labor (DOL) Estimate for California	Employment Development Department (EDD) Estimate
1st Payment Rate	Dec 2019 (1st week)	0.8485	0.78
Recipiency Rate	Dec 2019 (1st week)	0.2279	0.2098
Exhaustion Rate	Dec 2019 (1st week)	0.0287	0.0257
1st Payment Rate	Dec 2020 (1st week)	0.8028	0.75
Recipiency Rate	Dec 2020 (1st week)	0.9664	0.8500
Exhaustion Rate	Dec 2020 (1st week)	0.0022	0.0029

Notes: N = 50 (DOL), 58 (EDD). Each cell represents the mean of the measure of access.

The only case in which the EDD estimate is significantly larger (32% larger) is the exhaustion rate in 2020. In this case, we suspect our approach in the DOL data underestimates the exhaustion rate. To calculate the number of claimants exhausting in the DOL data, we use the number of final payments for the program that would be the last one available to most claimants, which was EB in December 2020. This likely misses some claimants who exhausted PEUC and were not eligible for EB.[12]

Aside from exhaustion rates, the remaining EDD estimates are generally 6 to 12 percent lower than DOL. The main differences in estimates for recipiency rates and 2019 exhaustion rates arise from the fact that the DOL data for continuing claims are reported by the processing week while in EDD we use the week of unemployment to count continuing claims. Finally, the basis of discrepancy in the first payment measure is that in the EDD data we link individual-level data for new claimants to payment information to find the first payment rate; however, in the DOL data, we must rely on aggregate monthly numbers.

[12] For more details on EB (FED-ED) eligibility in California see here.

Correlations Among Access Measures

Table 3 presents correlations among the three access measures in 2019 and 2020 for both cross-state and within-California analyses.

The correlations we detect are consistent with the mechanical relationship hypothesized between recipiency rates and either first payment rates or exhaustion rates.[13] Holding other factors constant, the more likely a community's residents are to receive first payments, the higher the recipiency rate should be. Indeed, we detect a positive correlation between recipiency rates and first payment rates. Conversely, states or counties with higher rates of exhaustion have lower recipiency rates. This is also to be expected, because any time a claimant exhausts UI but remains unemployed, this event mechanically lowers the recipiency rate.[14]

Whereas the two correlations with recipiency rates are consistent with the predictions of our conceptual model, the model did not offer a clear prediction as to the sign of the correlation between exhaustion rates and first payment rates. In the data, we typically find this correlation to be negative. In other words, states or counties where more claims were paid are also those in which a lower share of claimants exhausted benefits. The only exception is the within-California correlation for 2020, in which we observe a positive correlation between first payment and exhaustion rates.

One hypothesis that could be explored in future research is that this correlation may be driven by policy differences in general UI generosity across states. More generous policies, broadly defined, may jointly increase both first payment rates and decrease exhaustion, leading to the negative correlation. However, the fact that similar correlations exist between rates of first payments and exhaustions across California counties in 2019 is not consistent with the hypothesis that differences across states reflect different policies.[15]

[13] These were hypotheses 2 and 3 from Section 1.1.

[14] The magnitude of the expected direction within-California for 2020 is very small with a correlation of only 0.01.

[15] Although not supported by our data at present, it is worth noting that alternative theories could have predicted a correlation between rates of first payments and exhaustions of the opposite sign. For instance, borrowing from the selection framework of (Nichols & Zeckhauser, 1982), if states differed substantially in the ordeal costs they chose to impose on UI claimants, one might imagine that states with the lowest payment rates would have only the most qualified or motivated claimants collecting UI. In the context of such a model, it might not be surprising to find that in such high-ordeal states, those motivated claimants who succeed in establishing claims are quicker to find jobs prior to exhausting. However, the correlations we see in the data are contrary to this prediction.

Table 3: Correlations Among Key Access Measures

Panel A: Within California (County-level), December 2019

	Recipiency Rate	1st Payment Rate	Exhaustion Rate
Recipiency Rate	1		
1st Payment Rate	0.6231	1	
Exhaustion Rate	-0.4313	-0.5069	1

Panel B: Within California (County-level), December 2020

	Recipiency Rate	1st Payment Rate	Exhaustion Rate
Recipiency Rate	1		
1st Payment Rate	0.1589	1	
Exhaustion Rate	-0.0149	0.2353	1

Panel C: Across States, December 2019

	Recipiency Rate	1st Payment Rate	Exhaustion Rate
Recipiency Rate	1		
1st Payment Rate	0.4895	1	
Exhaustion Rate	-0.3420	-0.1595	1

Panel D: Across States, December 2020

	Recipiency Rate	1st Payment Rate	Exhaustion Rate
Recipiency Rate	1		
1st Payment Rate	0.2884	1	
Exhaustion Rate	-0.6394	-0.2551	1

Notes: N = 50 (state), N = 58 (county). Each cell represents the correlation between the two measures of access, weighted by population in 2019.

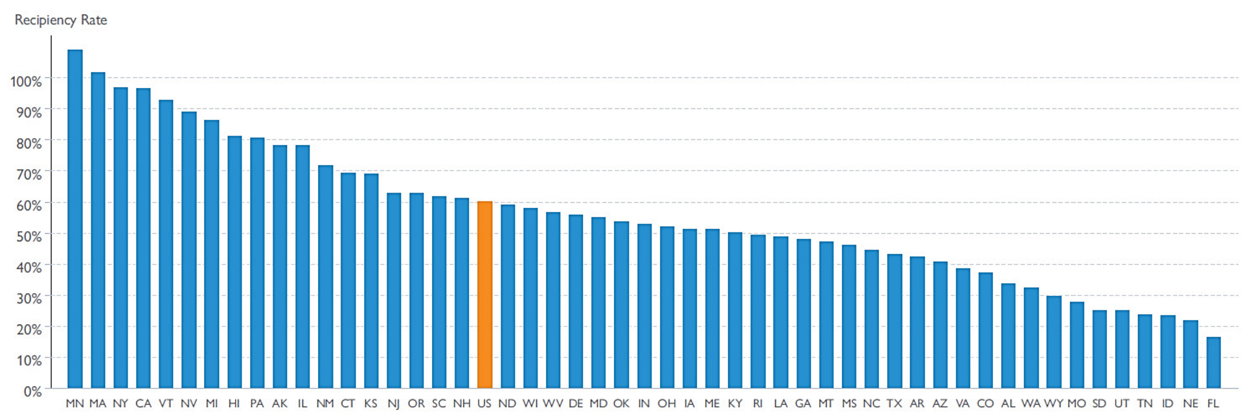
A potential explanation for the appearance of negative correlation across counties in 2019 that could be tested in future work could be that differences in both variables are driven in some part by the composition of workers. For instance, consider a county in which many workers have a low labor force attachment. We might expect to see low rates of first payment in this county due to the fact that many jobless workers do not have sufficient prior earnings to successfully establish a claim. But among those who do establish claims, we might also expect to see a higher rate of exhaustion, either because benefit duration has been reduced below California's 26-week maximum due to low prior earnings, or because the worker continues to have difficulty finding a job. In 2020 however, we observe a positive correlation. The main change in 2020 is that due to extension programs, claimants who otherwise would have low benefit durations instead benefited from longer durations which mechanically lowers exhaustion rates.

2.1: Recipiency Rates Among the Unemployed

Recipiency Rates Across the U.S.

Across the United States, we estimate that 60% of Americans who were unemployed in December of 2020 collected regular UI benefits. Figure 2 shows that the national average masks substantial heterogeneity across states. In some states — such as MN, MA, NY, and CA — the number of UI claimants was essentially comparable to the number of people thought to be unemployed (with a recipiency rate of at least 90%). In contrast, TN, ID, NE, and FL all saw recipiency rates of less than one quarter, meaning that even at the height of the pandemic, over three-quarters of unemployed workers were not collecting benefits. Figure 3 maps recipiency rates across states. In general, UI recipiency rates tended to be lower in the Southern and mid-Western parts of the country.[16]

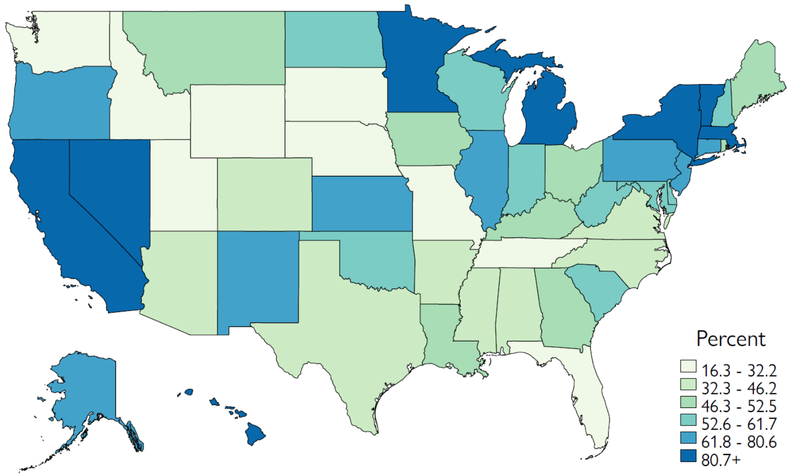
Figure 2: Recipiency Rates Across States, Bar Graph



Notes: N = 50. Source = DOL. The blue bars represent the recipiency rates across states for the week of December 5th, 2020. The orange bar represents the US average recipiency rate weighted by population in 2019. The recipiency rate is the number of continuing claims paid from the DOL divided by the number of U6 unemployed from the CPS. For more details on the recipiency rate, please refer to Section 1.2 of the text.

[16] Figures A1 and A2 plot the same bar graph and map using U3 unemployment instead of U6 in the Recipiency Rate and show very similar patterns. Although using the U3 measure of unemployment indicates that many states saw more than 100% of unemployed people receiving UI benefits, a proper interpretation is more nuanced. The fact that the numerator in some cases exceeds the denominator is not surprising because eligibility was expanded for UI benefits during the pandemic beyond those who would normally be considered unemployed under the U3 definition.

Figure 3: Recipiency Rates Across States, Map



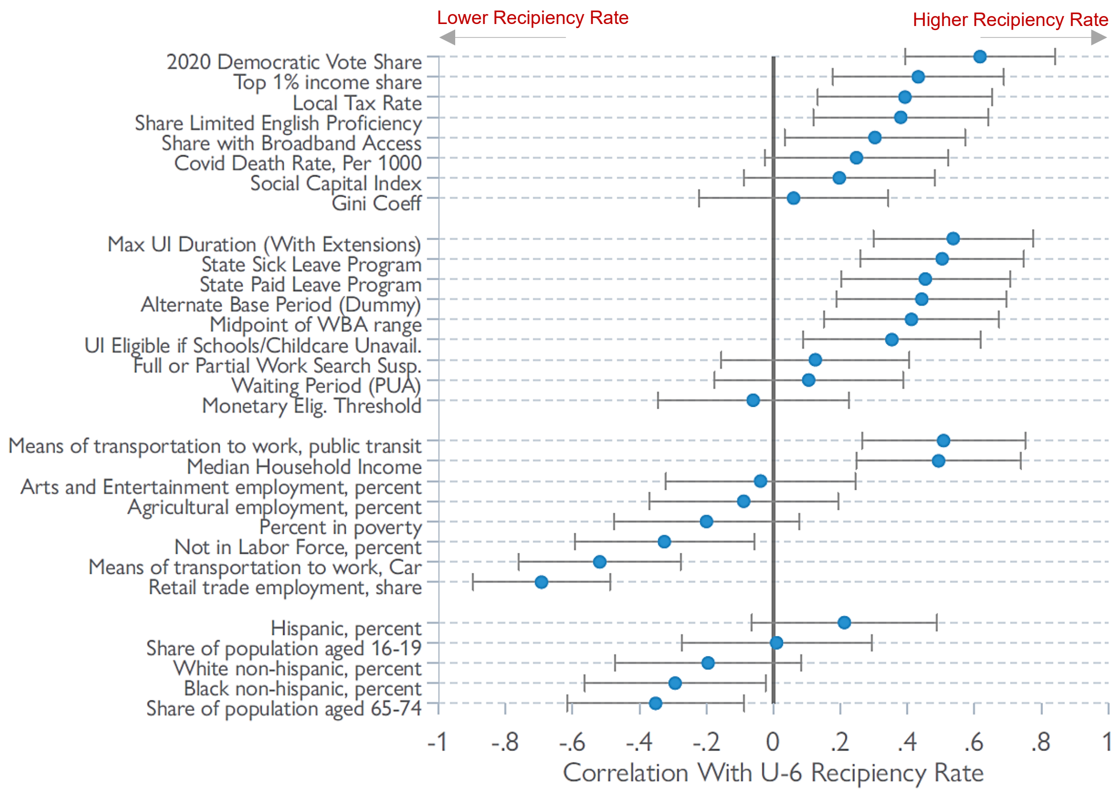
Notes: N = 50. Source = DOL. The colors represent the recipiency rates (in percent) across states for the week of December 5th, 2020. The recipiency rate is the number of continuing claims paid from the DOL divided by the number of U6 unemployed from the CPS. For more details on the recipiency rate, please refer to Section 1.2 of the text.

To better understand the sources of this state-level variation, Figure 4 presents correlations and 95% confidence intervals[17] of recipiency rates with other state-level policy and socioeconomic factors.[18] On the socioeconomic side, states that experienced higher recipiency rates during the pandemic tended to be wealthier, as evidenced by a strong positive correlation with median household income. States that had a higher Democratic vote share in the last presidential election also had higher recipiency rates. States with higher shares of Black residents had lower recipiency rates during the pandemic. This pattern sheds light on racial disparities in access to the American UI system documented by a growing historical and qualitative literature (Edwards, 2020; Fields-White et al., 2020).[19] A number of state-level policies were also highly correlated with differences in recipiency rates. States that afforded claimants longer Potential Benefit Duration (PBD) had substantially higher recipiency rates, as did states with alternative base periods. States with public sick or paid leave programs also had higher rates of recipiency. One hypothesis for this correlation that could be tested further is that this reflects that states with generous UI policies also have other generous labor-related policies. Overall, although not causal evidence, these descriptive correlations are consistent with state-level policies affecting access to UI during the pandemic.[20]

---

[17] All statistically significant results are significant at the 95% confidence level.
[18] Figure A3 plots the correlations between each covariate and the U3 based version of the Recipiency Rate. The results are nearly identical.
[19] An original aim of this study was to quantify the extent to which racial and ethnic disparities at the national level could be explained by low rates of access in states with certain racial and ethnic demographic compositions. As discussed in Section 3, we were unable to answer this question because the race and ethnicity information contained in the DOL data turned out to be inconsistent.
[20] Figure A3 plots the correlations between each covariate and the U3 based version of the Recipiency Rate. The results are nearly identical.

Figure 4: Recipiency Rates Across States, Correlations



Note: N = 50. Source = DOL and ACS. Each dot represents the correlation between the covariate and recipiency rate in December 2020 weighted by population in 2019. All variables are measured at the state level. Error bars represent the 95% confidence interval. The recipiency rate is the number of continuing claims paid from the DOL divided by the number of U6 Unemployed from the CPS. For more details on the recipiency rate and the sources of the covariates, please see Section 1.2 of the text and the data appendix.

Although these findings are correlational, the magnitudes of the correlations of recipiency rates with policy variables are substantial in many cases. Consider, for instance, the cross-state relationship observed between state PBD and recipiency rates. In December of 2020, the state UI maximum PBD in NC was 12 weeks, whereas MA offered up to 30 weeks.[21] Unsurprisingly, recipiency rates were substantially lower in NC than MA – 44% vs 102%. Suppose for the purpose of a back-of-envelope calculation that the observational correlation between state maximum PBD and recipiency were causal. If all states had a PBD of 30 weeks, the national recipiency rate would grow from 60% to 77% – a 28% increase. This would result in about three million more jobless workers collecting UI benefits each week, totaling about $1.7 billion in benefits. While such a calculation should be interpreted with caution as there are many other factors that differ across states, the magnitude of this difference suggests there was likely great potential for state-level policies to influence recipiency rates during the pandemic.

[21] Massachusetts State UI PBD increases from 26 to 30 weeks when unemployment is high.

While a causal analysis of these policies is beyond the scope of the present work,[22] we explore in Figure 5 an analysis of how these state-level correlations have changed around the time of the pandemic. For each covariate, we contrast the correlation both with recipiency in December of 2019 and with recipiency in December of 2020. Despite the fact that recipiency rates have risen substantially during the pandemic, the relative geographic patterns are surprisingly stable. The types of states that had high recipiency rates before the pandemic also had high recipiency rates during the pandemic.[23] Although no differences in the correlations are statistically significant, it is worth noting that the ordinarily high correlation between Weekly Benefit Amount (WBA) generosity and recipiency rates has fallen considerably during the pandemic. This would be the direction one would expect based on the common nature of the federal added benefits supplements across states (which reduces the relative difference in WBAs across states), combined with the impact of benefit generosity on take-up (P. Anderson, 2020; P. M. Anderson & Meyer, 1997).

Insights from Within CA

Measuring recipiency rates for regions within California is an important but difficult task. Although we have precise measures of how many Californians collected benefits from a given geographic unit, estimating the number of unemployed workers in that place at that time is more cumbersome. In this analysis, we rely on official county-level estimates from the Bureau of Labor Statistics Local Area Unemployment Statistics (US Bureau of Labor Statistics, 2021). However, estimating recipiency rates this way is far from ideal due to the small sample size of the Current Population Survey (108,000 people) the LAUS estimates for unemployment at the sub-state level rely on certain measures of UI claims themselves.[24] While we have contrasted the LAUS county unemployment rates to comparable estimates based on the CPS microdata and found them to be similar, the fact remains that for many smaller geographic units the estimates are based on small samples and hence are prone to statistical noise. For this reason, the county-level estimates of UI recipiency rates presented below should be interpreted with caution.[25]

---

[22] There is scope for additional work to investigate more causal mechanisms that underlie these correlations. Building on the work of (Gould-Werth & Shaefer, 2013) that studied the role of alternative base periods in access to UI, more research is needed to leverage the large amount of natural time-series variations that occur in several of these policies across states.

[23] Figure A4 plots each states recipiency rate in 2019 and 2020, and demonstrates that, despite being noisy, states with higher recipiency rates in 2019 also had higher recipiency rates in 2020.

[24] For more information, see the LAU.S. methodology note: https://www.bls.gov/lau/laumthd.htm.

[25] In our ongoing series of policy briefs, we have compared geographic patterns of recipiency rates using the LAU.S. county-level definition of unemployment to the tract-level unemployment estimates near the start of the pandemic of (Ghitza & Steitz, 2020). We have not detected meaningful differences in the spatial correlations using either measure of unemployment.

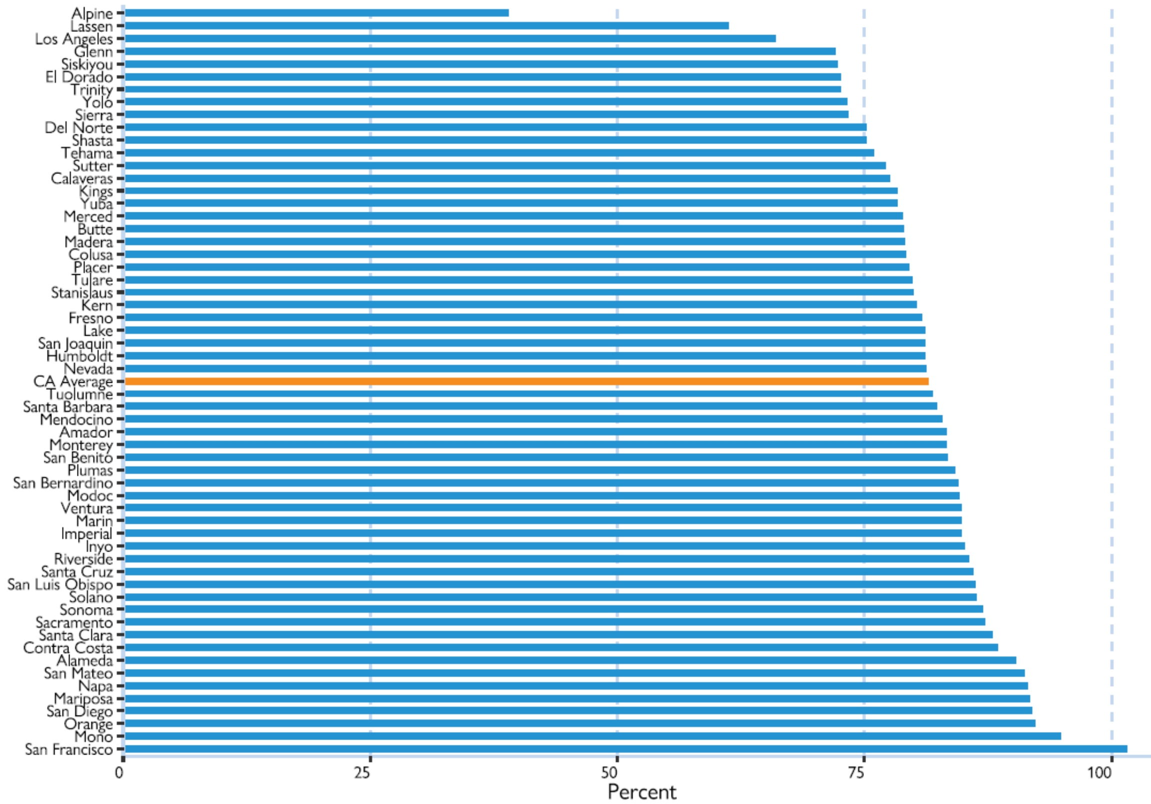
Figure 5: Recipiency Rates Across States, Correlations, 2019 vs 2020

Notes: N = 50. Each dot represents the correlation between the covariate and the recipiency rate in December 2019 and December 2020 weighted by population in 2019. All variables are measured at the state level. Error bars represent the 95% confidence interval. The recipiency rate is the number of continuing claims paid from the DOL divided by the number of U6 unemployed from the CPS. For more details on the recipiency rate and the sources of the covariates, please see Section 1.2 of the text and the data appendix.

Analogous to Figure 2, Figure 6 shows how recipiency rates varied within California. Based on the comparisons of UI claimants to LAUS unemployment rates (re-scaled to mirror U-6), Los Angeles County has by far the lowest recipiency rate among large counties in California. Figure 7 maps recipiency rates across each of California's 58 counties. Figures 6 and 7 also demonstrate substantially less variation in recipiency rates across counties than across states.[26] This could be a consequence of the UI program parameters being constant across counties, but substantially different across states.

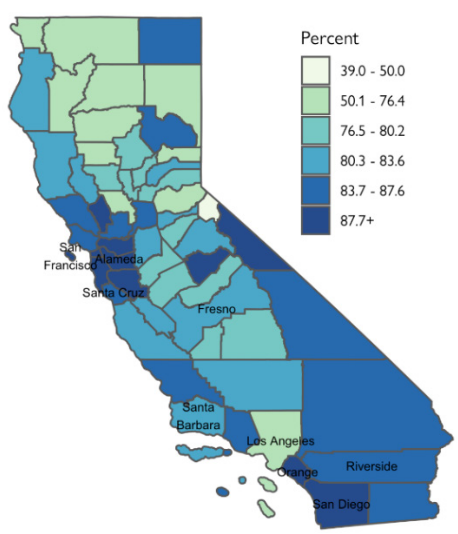
[26]Figures A7 and A8 shows how this variation changed over time and demonstrates that the variation across states and counties increased during the pandemic.

Figure 6: Recipiency Rates Within California, County-Level Bar Graph



Notes*:* N = 58. Source = EDD. The blue bars represent the recipiency rates for all the counties in December 2020. Orange bar represents the California average Recipiency Rate weighted by population. The recipiency rate is the number of continuing claims paid from EDD divided by the number of U6 unemployed from the CPS and LAUS. For more details on the recipiency rate, please see Section 1.2 of the text.

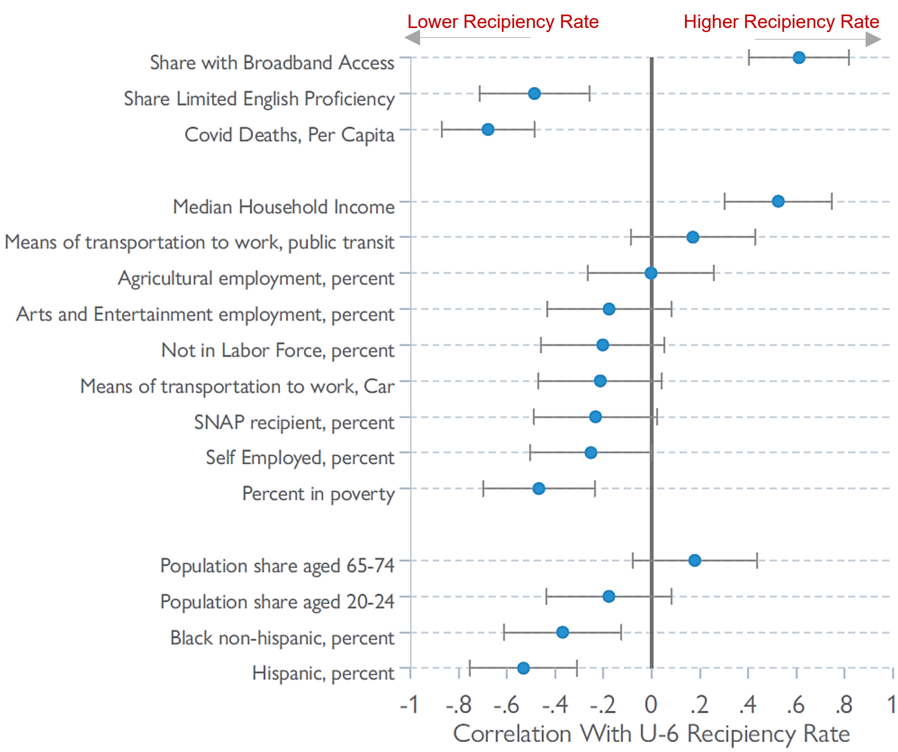
Figure 7: Recipiency Rates Within California, County-Level Map



Notes: N = 58. Source = EDD. The colors represent the U6 recipiency rate (in percent) across counties in December 2020. The recipiency rate is the number of continuing claims paid from EDD divided by the number of U6 Unemployed from the CPS and LAUS. For more details on the recipiency rate, please see Section 1.2 of the text.

Figure 8 shows county-level correlations and 95% confidence intervals of recipiency rates with socioeconomic indicators. Similar to our findings across states, higher-income counties also saw higher rates of UI recipiency. Counties with higher rates of COVID-19 deaths saw lower rates of recipiency, as did those counties with higher shares of Hispanic residents. We find that counties with more broadband access had substantially higher rates of UI recipiency, which points to the importance of technological gaps in access to UI during the pandemic. We also find that counties with more residents with limited English proficiency had lower rates of UI recipiency, which is consistent with reports that language barriers may also have played a role in limiting access (Hellerstein, 2020). Many of these correlational findings corroborate the more qualitative conclusions of Fields-White et al. (2020) on the role that barriers to access during the pandemic have played in widening racial disparities, including stigma, burdens to produce documentation, and the digital divide. Although an authoritative dissection of the roots of these differences is beyond the scope of the current study, a growing body of quantitative and qualitative evidence (Fields-White et al., 2020; Gould-Werth, 2016; Shaefer, 2010) suggests that both legal eligibility and more nuanced barriers to accessibility of UI have played important roles in determining UI recipiency rates.

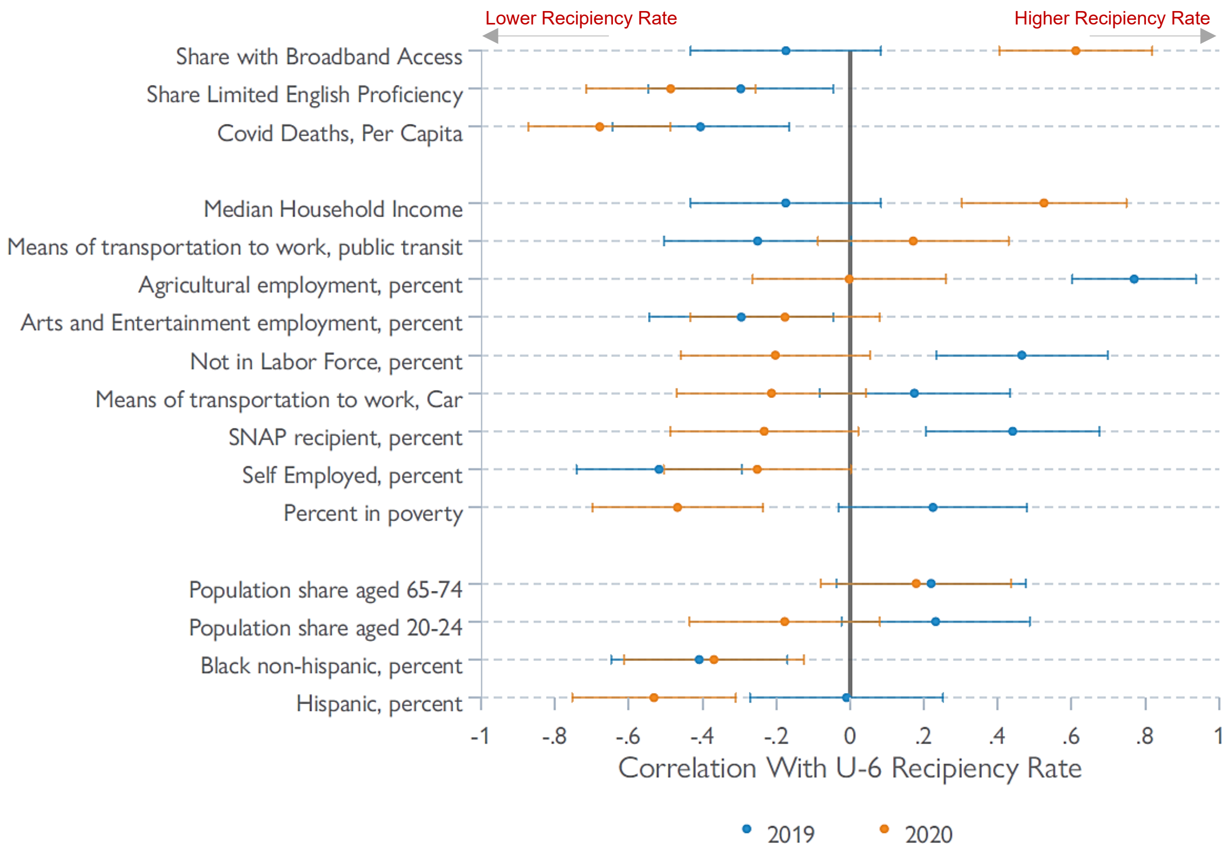
Figure 8: Recipiency Rates Within California, County-Level Correlations



Notes: N = 58. Source = EDD and ACS. Each dot represents the correlation between the covariate and UI recipiency rate in December 2020 weighted by population in 2019. All variables are measured at the county level. Error bars represent the 95% confidence interval. The recipiency rate is the number of continuing claims paid from EDD divided by the number of U6 Unemployed from the CPS and LAUS. For more details on the recipiency rate and the definitions of the covariates, please see Section 1.2 of the text and the data appendix.

Turning to the time dimension of recipiency rates within California, Figure 9 shows how these correlations have changed over the course of the pandemic. Whereas correlations across states have been relatively stable, correlations across counties have changed. The extent to which this may be due to differences in how LAUS has imputed unemployment rates should be investigated further before drawing firm conclusions. Still, taking these available estimates at face value, our analysis indicates that the strong positive relationship between recipiency rates and counties' median income and broadband access may be relatively new phenomena, as these correlations were not detectable in 2019. As with the state-level analysis, a more carefully controlled time-series analysis should be conducted prior to attributing a causal relationship from these cross-sectional correlations.

Figure 9: Recipiency Rates Within California, County-Level Correlations, 2019 vs 2020



Notes: N = 58. Source = EDD and ACS. Each dot represents the correlation between the covariate and the recipiency rate in December 2019 and December 2020 weighted by population in 2019. All variables are measured at the county level. Error bars represent the 95% confidence interval. The recipiency rate is the number of continuing claims paid from EDD divided by the number of U6 unemployed from the CPS and LAUS. For more details on the recipiency rate and the sources of the covariates, please see Section 1.2 of the text and the data appendix.

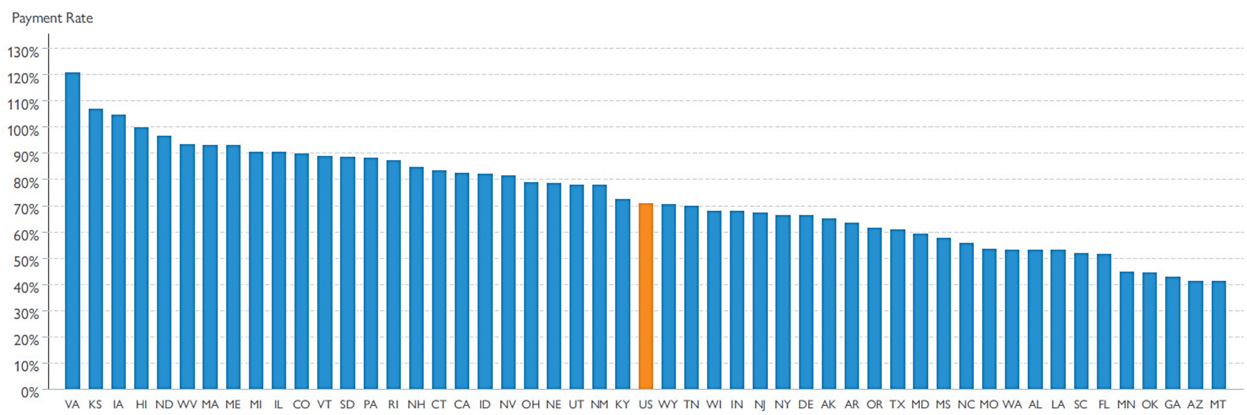
Given the stark differences across geographic regions in UI recipiency rates, we next turn to analyzing geographic differences in rates of first payments.

2.2: First Payment Rates Among Claimants

First Payment Rates Across the U.S.

At the national level, we estimate that about 70% of new initial claims filed in the first two quarters of 2020 resulted in first payments. This measure of access varied dramatically across states, although it should be noted that there is noise in this calculation in the DOL data because we are relating first payments issued in a month to new initial claims filed in a month (which are not necessarily the same claims). Still, Figure 10 shows that states essentially span the entire range from nearly 40% to approximately 100%.[27] Among the states that paid the highest share of claims in the first half of 2020 were VA, KS, IA, and HI, whereas MT, AZ, and GA were among the lowest. Figure 11 maps payment rates across states.

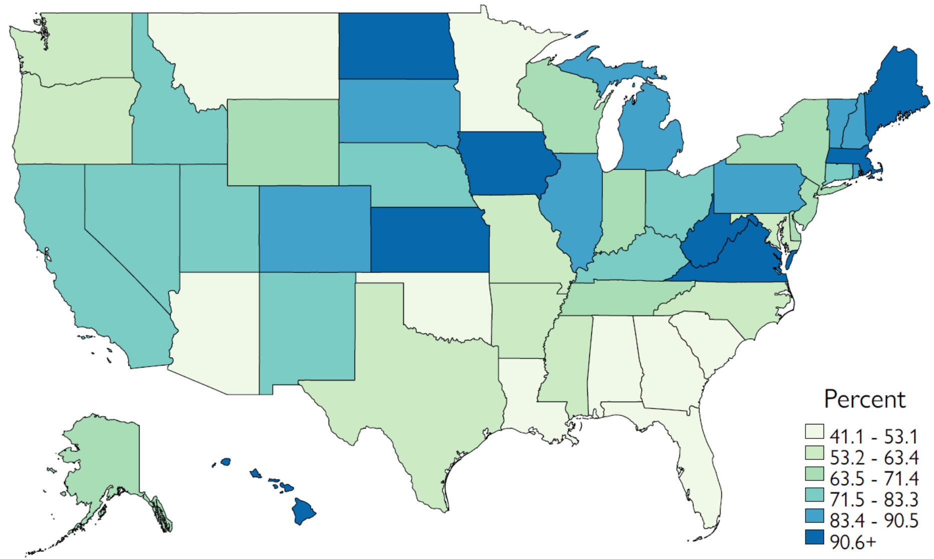
Figure 10: First Payment Rates Across States, Bar Graph



Note: N = 50. Source = DOL. The blue bars represent the first payment rate across states for 2020Q1 + 2020Q2 (January through June). The orange bar represents the US population weighted average. The first payment rate is the number of first claim payments divided by the number of new initial claims. For more details on the first payment rate, please refer to Section 1.2 of the text.

[27] The fact that some states are above 100% is an artifact of how DOL reports claims filed in a month and claims paid in a month, but these are not necessarily the same claims. This is a limitation that we face in our cross-state analysis but not for our within-California analysis relying on microdata.

Figure 11: First Payment Rates Across States, Map



Notes: N = 50. Source = DOL. The colors represent the first payment rates (in percent) across states for 2020Q1 + 2020Q2 (January to June). The first payment rate is the number of first claim payments divided by the number of new initial claims. For more details on the first payment rate, please refer to Section 1.2 of the text.

Figure 12 shows how the heterogeneity in first payment rates covaries with our set of state-level covariates[28]. Certain state-level policies appear to relate to first payment rates in the expected directions. In states that allow claims to be established under alternative base period formulas, more claimants get paid. Although states with longer UI durations also see a larger share of claimants paid, we do not detect a significant correlation between the share of claimants paid and monetary eligibility threshold. This is surprising, since a higher monetary eligibility threshold implies that (all else equal) fewer claimants are monetary eligible and therefore fewer claims will receive a first payment.[29] However, there are other reasons for a claim to go unpaid, including non-monetary eligibility criteria, short unemployment spells, or claimants failing to certify for benefits for other reasons. These scenarios may be less common in states with higher monetary eligibility thresholds. In general, states that paid a higher share of claims during the start of the pandemic tended to be more affluent (as measured by median household income or poverty rates) and have slightly more economic inequality (evidenced by the negative correlation of first payment rates with the Gini coefficient). States with a higher share of Black workers paid out a statistically significantly lower share of claims, though we did not detect a significant correlation with Hispanic share.

---

[28] All statistically significant results are significant at the 95% confidence level.

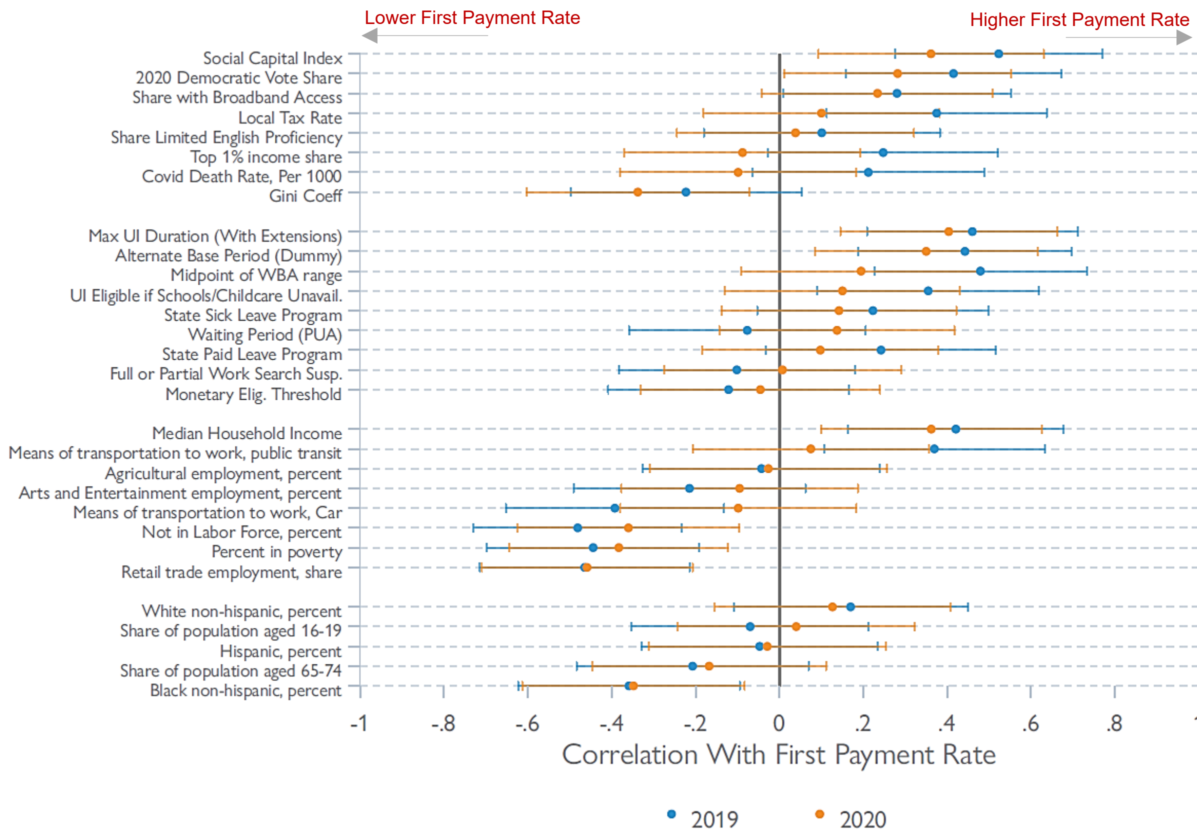
[29] A monetary eligibility threshold is the minimum amount of earnings that a jobless worker must have earned in the base period in order to establish a UI claim. The monetary eligibility threshold in January 2020 ranged from $130 in Hawaii to $7,000 in Arizona.

Figure 12: First Payment Rates Across States, Correlations

Notes: N = 50. Source = DOL and ACS. Each dot represents the correlation between the covariate and the first payment rate in Q1 and Q2 2020 weighted by population in 2019. All variables are measured at the state level. Error bars represent the 95% confidence interval. The first payment rate is the number of first claim payments divided by the number of new initial claims. For more details on the first payment rate measure and the sources of the covariates, please see Section 1.2 of the text and the data appendix.

Figure 13 shows how the predictors of first payment rates across states have changed. We do not find any correlations that have changed significantly in a statistical sense, though this non-result could largely be due to the imprecision with which this variable is measured in the DOL data. If these cross-state patterns could be more precisely measured in future work, it could help establish the extent to which states' decisions to implement emergency policies during the pandemic have increased access to UI.

Figure 13: First Payment Rates Across States, Correlations, 2019 vs 2020

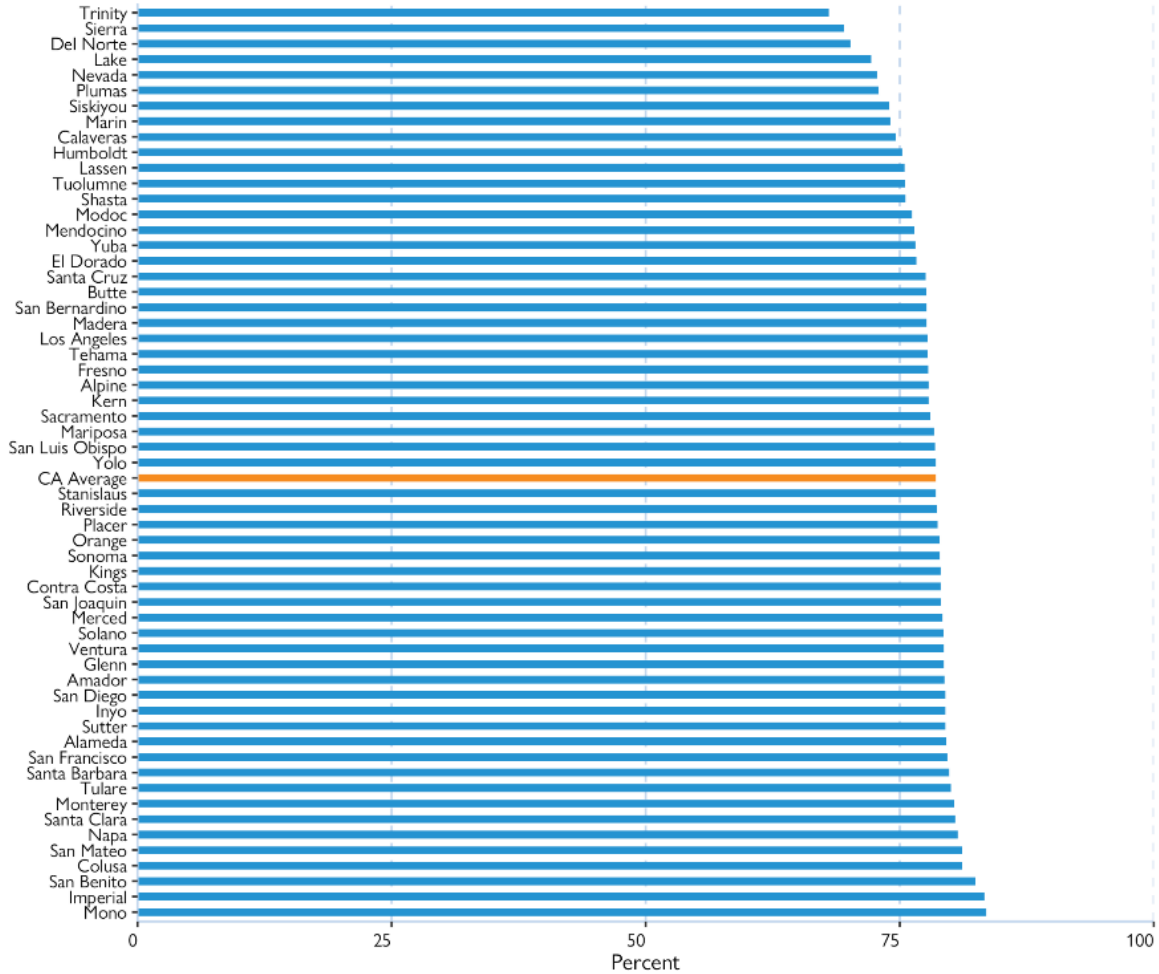


Notes: N = 50. Source = DOL and ACS. Each dot represents the correlation between the covariate and the first payment rate in Q1 and Q2 2019 and 2020 weighted by population in 2019. All variables are measured at the state level. Error bars represent the 95% confidence interval. The first payment rate is the number of first claim payments divided by the number of new initial claims. For more details on the first payment rate and the sources of the covariates, please see Section 1.2 of the text and the data appendix.

Insights from within CA

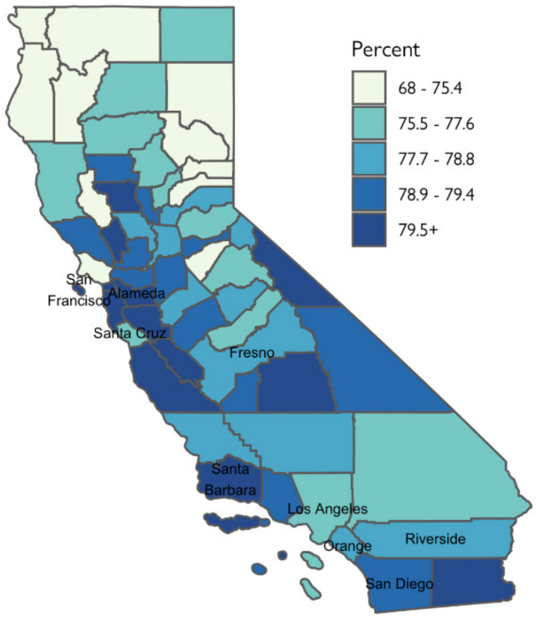
Relative to the amount of variation in first payment rates across states, the variation in first payment rates across California's counties is more modest. The sample of the first payment analysis includes claimants with regular new initial claims in the second quarter of 2020. Figure 14 plots the rate of first payments in each of California's 58 counties, and Figure 15 maps this rate for each county. Trinity County saw the lowest rate of first payments in the second quarter of 2020 (about 68%), with low rates also coming from Sierra, Del Norte, and Lake. Among the counties with the highest share of claims paid were Mono, Imperial, and San Benito (83%, 83%, and 82% respectively). Los Angeles County, which ranked among the lowest counties in terms of recipiency rates as benchmarked in relation to LAUS estimates of unemployed people, ranked near the middle in terms of the share of claims from its residents that have been paid (77%).

Figure 14: First Payment Rates Within California, County-Level Bar Graph



Notes: N = 58. Source = EDD. Each blue bar represents the first payment rate (in percent) in each county in Q2 of 2020. The orange bar represents the California average weighted by population in December 2019. The first payment rate is the number of first claim payments divided by the number of new initial claims. For more details on the first payment rate, please see Section 1.2 of the text.

Figure 15: First Payment Rates Within California, County-Level Map



Notes: N = 58. Source = EDD. The colors represent the first payment rate (in percent) for each county in Q2 2020. The first payment rate is the number of first claim payments divided by the number of new initial claims. Data is from EDD. For more details on the first payment rate, please refer to Section 1.2 of the text.

Figure 16 correlates counties' first payment rates with our standard county-level set of covariates[30]. By several measures, more affluent counties saw substantially higher rates of payments. Counties with higher income and fewer Supplemental Nutrition Assistance Program (SNAP) recipients or fewer people in poverty saw higher rates of payments among claimants. We also detect a positive relationship between broadband access and first payment rates.

[30] All statistically significant results are significant at the 95% confidence level.

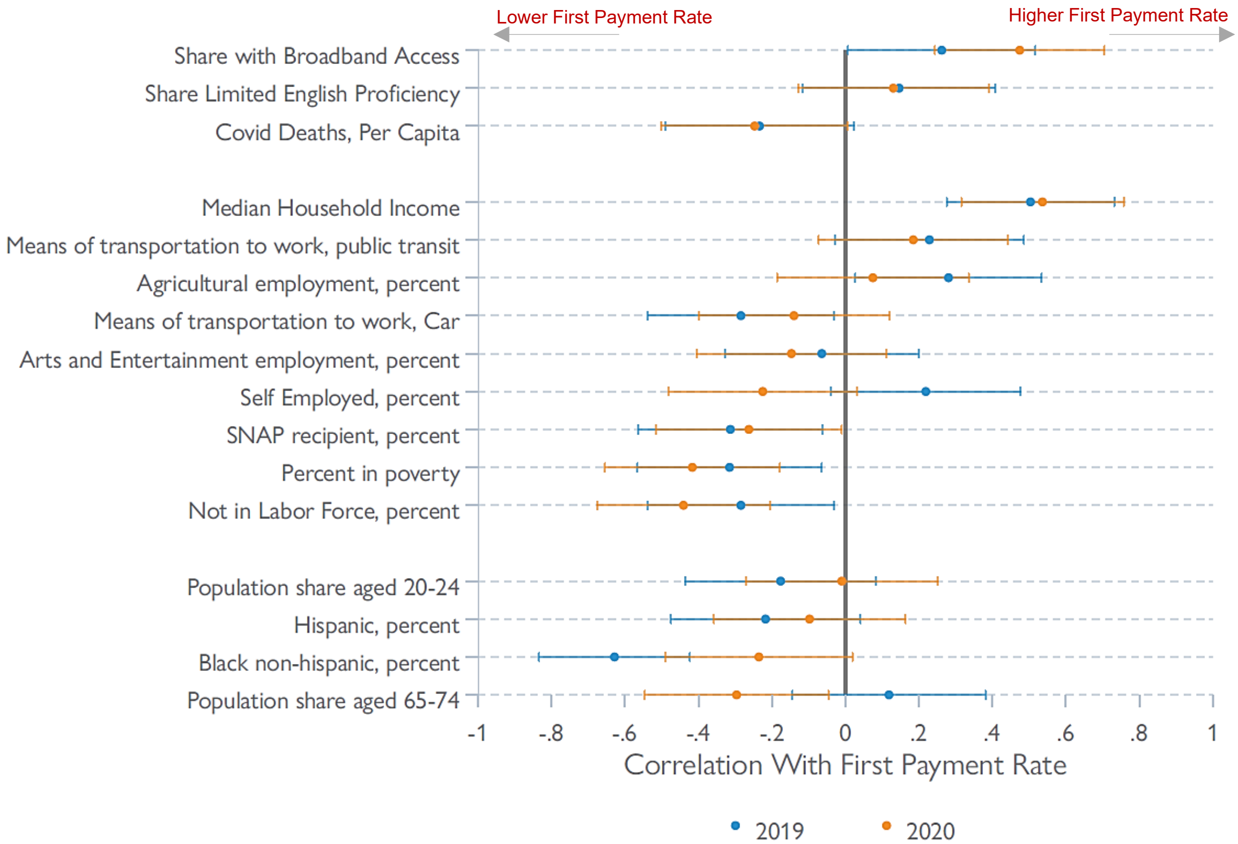
Figure 16: First Payment Rates Within California, County-Level Correlations

Notes: N = 58. Source = EDD and ACS. Each dot represents the correlation between the covariate and the first payment rate in Q2 2020 weighted by population in 2019. All variables are measured at the county level. Error bars represent the 95% confidence interval. The first payment rate is the number of new initial claimants who received at least one payment divided by the total number of new initial claimants in Q2 2020. For more details on the first payment rate measure and the sources of the covariates, please see Section 1.2 of the text and the data appendix.

Figure 17 contrasts the results of correlations from 2019 versus 2020 data. If anything, the correlation of this measure with geographic differences in race and ethnicity may have lessened during the pandemic. There is suggestive evidence that in 2019, counties with more Black residents used to have lower rates of payments, and that this correlation has decreased somewhat in the start of 2020. Separately, there is some evidence that prior to the pandemic, payment rates were higher in counties with more self-employed workers, but that this correlation has flipped during the pandemic. However, we are hesitant to read very much into the individual significance of these results on their own due to the number of hypotheses tested, which raises the likelihood for spurious correlations.

Having established geographic heterogeneity in the rate at which first payments were issued during and before the pandemic, the final stage of our analysis turns to exhaustion rates.

Figure 17: First Payment Rates Within California, County-Level Correlations, 2019 vs 2020



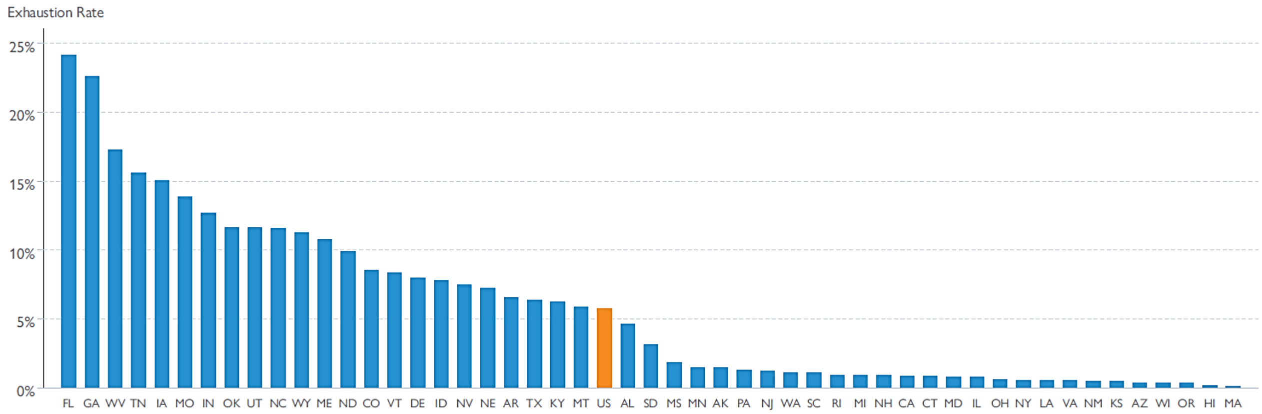
Notes: N = 58. Source = EDD and ACS. Each dot represents the correlation between the covariate and the first payment rate in Q2 2020 and Q2 2019 weighted by population in 2019. All variables are measured at the county level. Error bars represent the 95% confidence interval. The first payment rate is the number of new initial claimants who received at least one payment divided by the total number of new initial claimants in Q2 2019/2020. For more details on the first payment rate measure and the sources of the covariates, please see Section 1.2 of the text and the data appendix.

2.3: Exhaustion Rates

Exhaustion Rates Across the U.S.

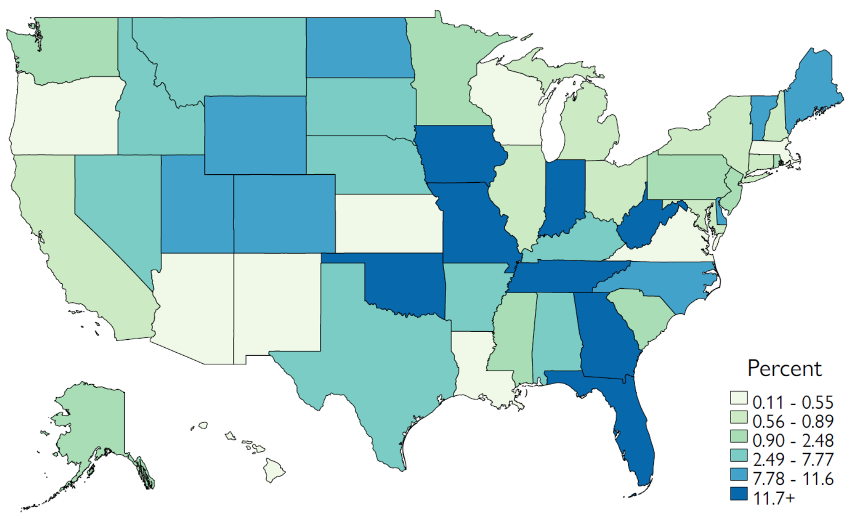
We estimate that in the first week of December of 2020, approximately 6% of Americans who were claiming UI benefits exhausted their benefits. The exhaustion rate varied substantially across states, with Florida and Georgia seeing 24% and 23% of their claimants exhausting, respectively. In contrast, 50% of states saw exhaustion rates of 3% or less. The top five states with the most exhaustions in December 2020 were Georgia, Texas, Florida, North Carolina, and California, and together they accounted for 52% of all exhaustions in the U.S. that month. Figure 18 plots a bar graph of exhaustion rates across states, depicted in map form in Figure 19.

Figure 18: Exhaustion Rates Across States, Bar Graph



Notes**:** N = 50. Source = DOL. The blue bars represent the percent of claimants who exhausted their benefits across states for the month of December 2020. The orange bar represents the US average weighted by population. The Exhaustion Rate is the number of claimants who exhaust their benefits divided by the number who received payments. For more details on the exhaustion rate and the sources of the covariates, please refer to Section 1.2 of the text.

Figure 19: Exhaustion Rates Across States, Map



Notes**:** N = 50. Source = DOL. The colors represent the percent of claimants who exhausted their benefits across states for the month of December 2020. The Exhaustion Rate is the number of claimants who exhaust their benefits divided by the number who received payments. For more details on the exhaustion rate and the sources of the covariates, please refer to Section 1.2 of the text.

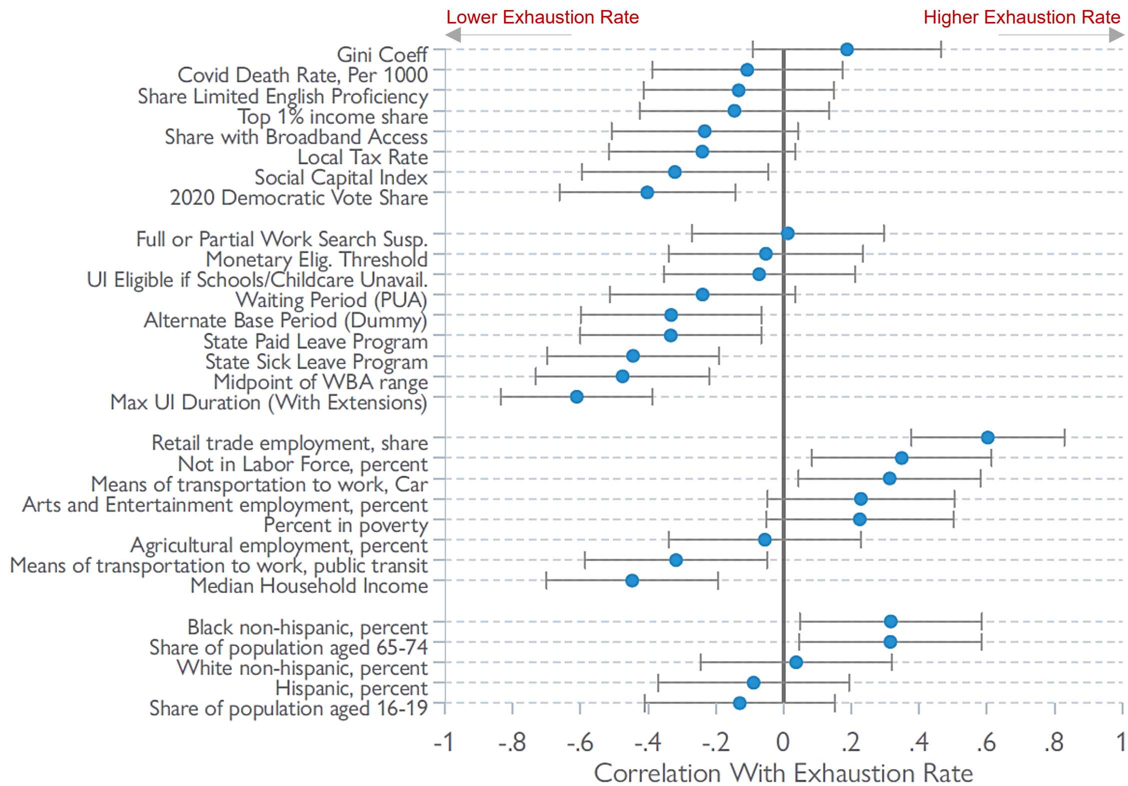
A wide variety of socioeconomic and policy variables are significantly correlated with differences in state-level differences in exhaustion rates during the pandemic.[31] Figure 20 presents these correlations. Of the covariates we studied, the strongest correlate of exhaustion rates was the maximum duration of UI benefits. Exhaustion rates were lower in states with more generous benefits (either in terms of duration or levels) and those that provided workers with sick leave programs (which may have functioned as alternatives to UI). In general, exhaustion rates were

---

[31] All statistically significant correlations are significant at the 95% confidence level.

also substantially lower in more Democratic-leaning states and states with more high-earners. Exhaustion rates were slightly higher in states with more Black residents and older residents.

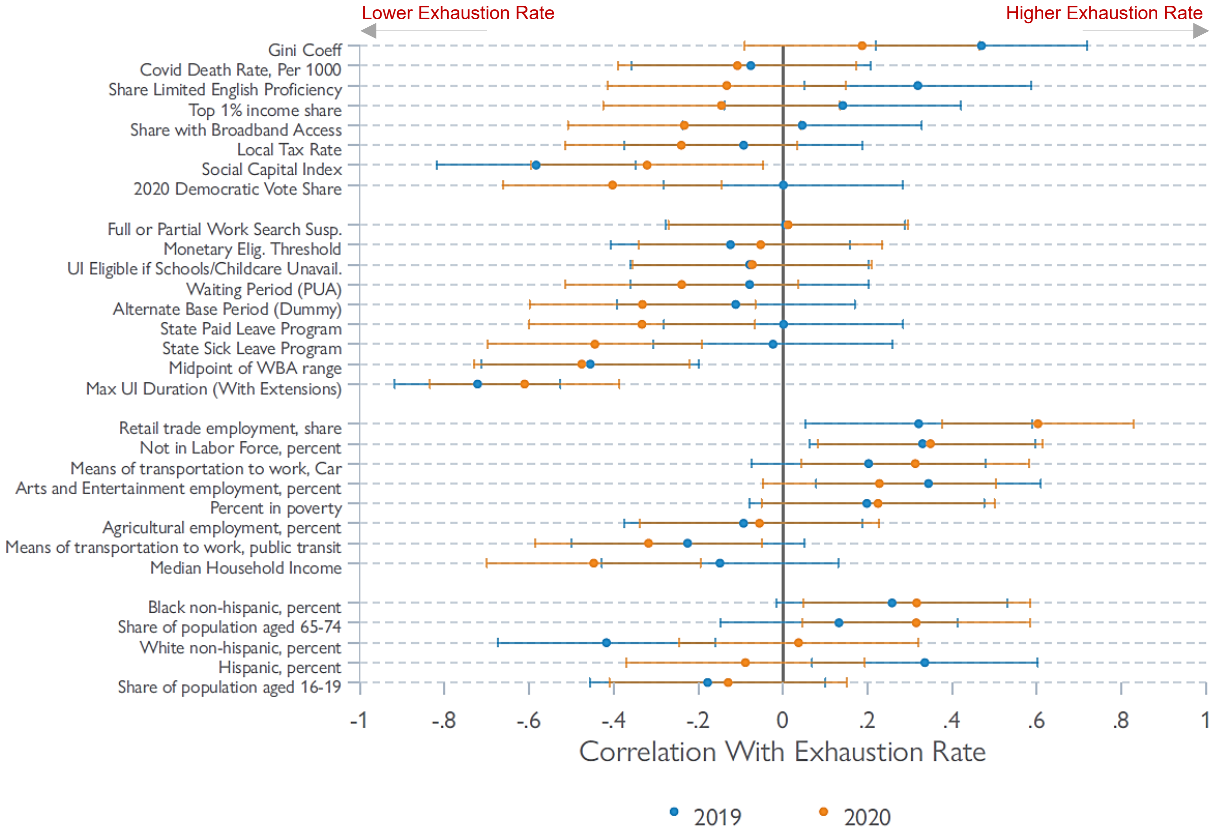
Figure 20: Exhaustion Rates Across States, Correlations



Notes: N = 50. Source = DOL and ACS. Each dot represents the correlation between the covariate and the exhaustion rate in December 2020 weighted by population in 2019. All variables are measured at the state level. Error bars represent the 95% confidence interval. The Exhaustion Rate is the number of claimants who exhaust their benefits divided by the number who received payments. For more details on the exhaustion rate and the sources of the covariates, please see Section 1.2 of the text and the data appendix.

Figure 21 contrasts the national landscape of exhaustion rates before and during the pandemic. Most notably, certain correlations have emerged during the pandemic that did not appear statistically significant at the 95% confidence level in 2019. In particular, the negative association between exhaustion rates and the presence of a state paid or sick leave program appears to have emerged during the pandemic. A hypothesis that could be tested in the future is that while these programs had little impact on UI exhaustion rates prior to the pandemic, they were useful stop-gap measures to prevent workers who were either too sick to work or otherwise occupied with caregiving responsibilities from exhausting UI benefits during the pandemic.

Figure 21: Exhaustion Rates Across States, Correlations, 2019 vs 2020



Notes: N = 50. Source = DOL and ACS. Each dot represents the correlation between the covariate and the exhaustion rate in December 2020 and December 2019 weighted by population in 2019. All variables are measured at the state level. Error bars represent the 95% confidence interval. The Exhaustion Rate is the number of claimants who exhaust their benefits divided by the number who received payments. For more details on the exhaustion rate and the sources of the covariates, please see Section 1.2 of the text and the data appendix.

Insights from within CA

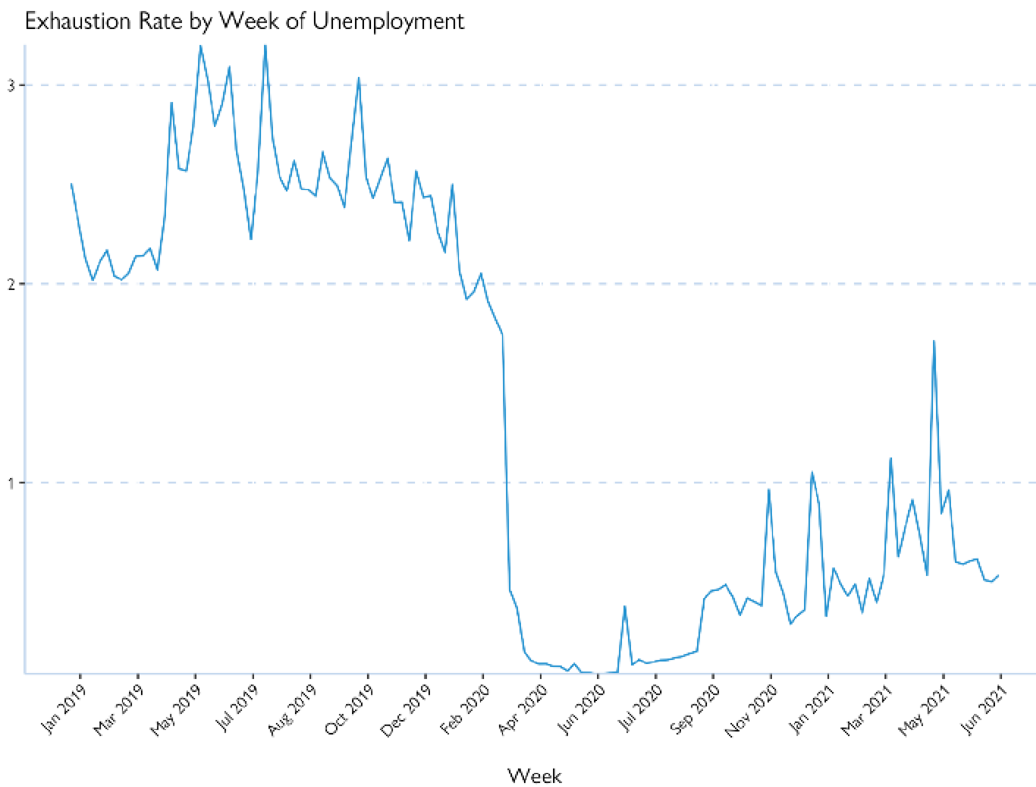
For our within-California analysis, we put forward two distinct measures of exhaustion rates. To mirror the definition of exhaustion rates we were able to operationalize in the DOL data, we first divide the number of claimants who exhausted UI in a given week by the total number of claimants who certified that week. Conceptually, this ratio is difficult to interpret. Although each claimant can count at most once in the numerator (during the week of exhaustion), the same individual would count toward the denominator for multiple weeks (during each week claimed). A more readily interpretable statistic is the share of UI entrants in a given week who will eventually exhaust UI. Because this statistic counts each claimant exactly once in the denominator (during the week of entry), it is more accurate. For the same reason, the more accurate measure tends to be higher than the traditional measure. A potential drawback is that it cannot be implemented nationally with available data.

Figure 22 plots how these two definitions of exhaustion rates have evolved in California during the pandemic. Whereas the number of California's claimants exhausting each week has typically amounted to less than 1% of that week's continuing claimants (Panels A and B), a very different story emerges when analyzing exhaustees as a share of the weekly entry cohort

(Panel C). Among Californians whose benefit years began during the pandemic, between 10-20% of these claimants have already exhausted benefits as of the end of June 2021. However, we anticipate these cohort exhaustion rates rose considerably since June because this analysis did not take into account the large effects the recent September 2021 benefits expiration had on these cohorts.[32]

Figure 22: Exhaustion Rates Within California, Weekly Resolution, 2019-present

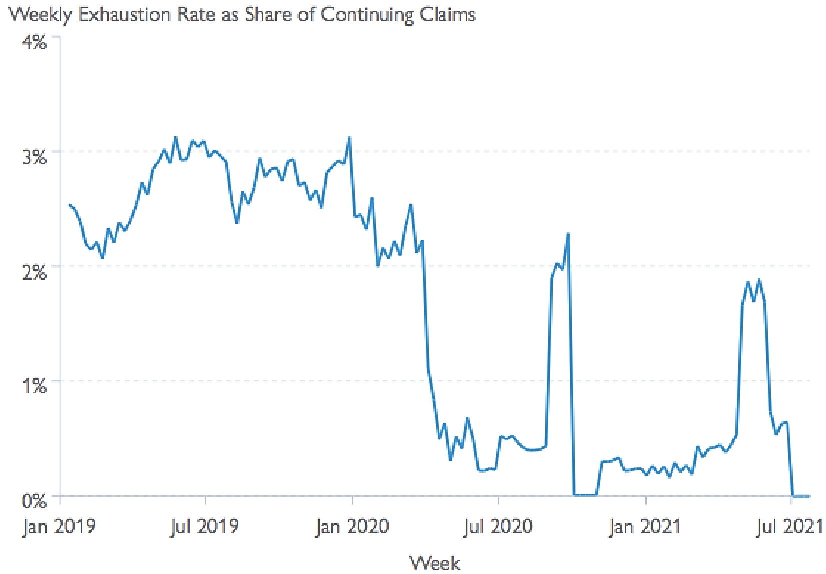
Panel A: Share of Claimants in California Exhausting as a Share of Weekly Continuing Claimants (from EDD)



Notes: N = 79. Source = EDD. The line represents the number of claimants who exhausted benefits each week divided by the number of continuing claims each week. The figure does not include claimants who only ever received PUA benefits. For more information about the exhaustion rate, please refer to Section 1.2 of the text.

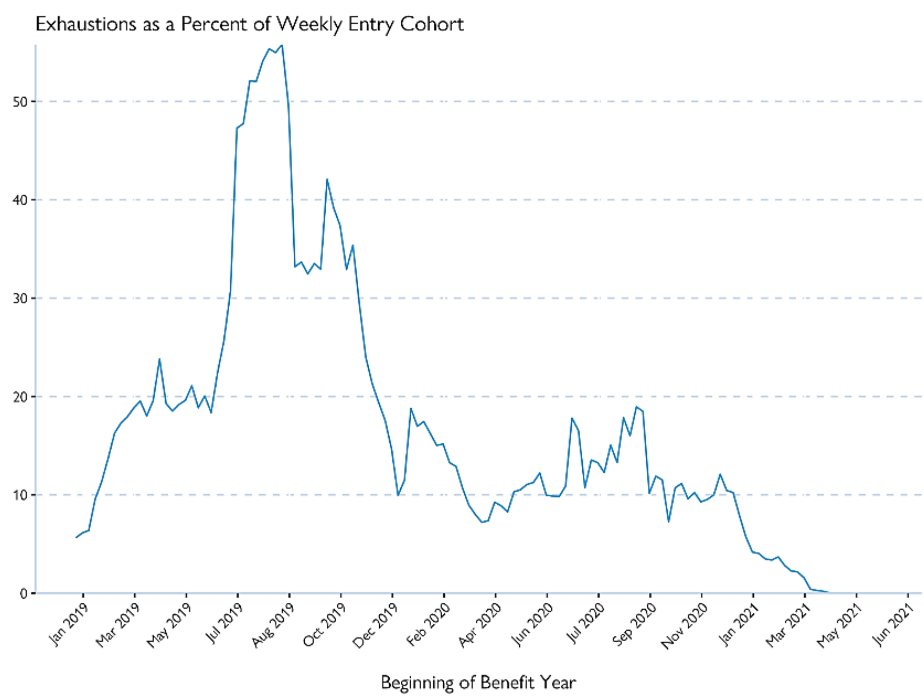
[32] We do not estimate the cohort exhaustion rate at the state level. To estimate the cohort exhaustion rate, one needs to find the size of each cohort and the number of exhausted claimants in the related cohort. To calculate such a rate, we need to make assumptions based on PBD. The main reason for avoiding using DOL data to calculate cohort exhaustion rate is the substantial disparities in PBD, especially post COVID with extension programs.

Panel B: Share of Claimants in California Exhausting as a Share of Weekly Continuing Claimants (from DOL)



Notes: N = 79. Source = DOL. Weekly exhaustion rate for California from DOL data from 2019 to present. Calculated by dividing the number of monthly exhaustions by 4 to get a weekly estimate, and then dividing each week's number of continuing claims by this weekly exhaustion value.

Panel C: Number of Claimants in California Exhausting as a Share of Weekly Entry Cohort (from EDD)



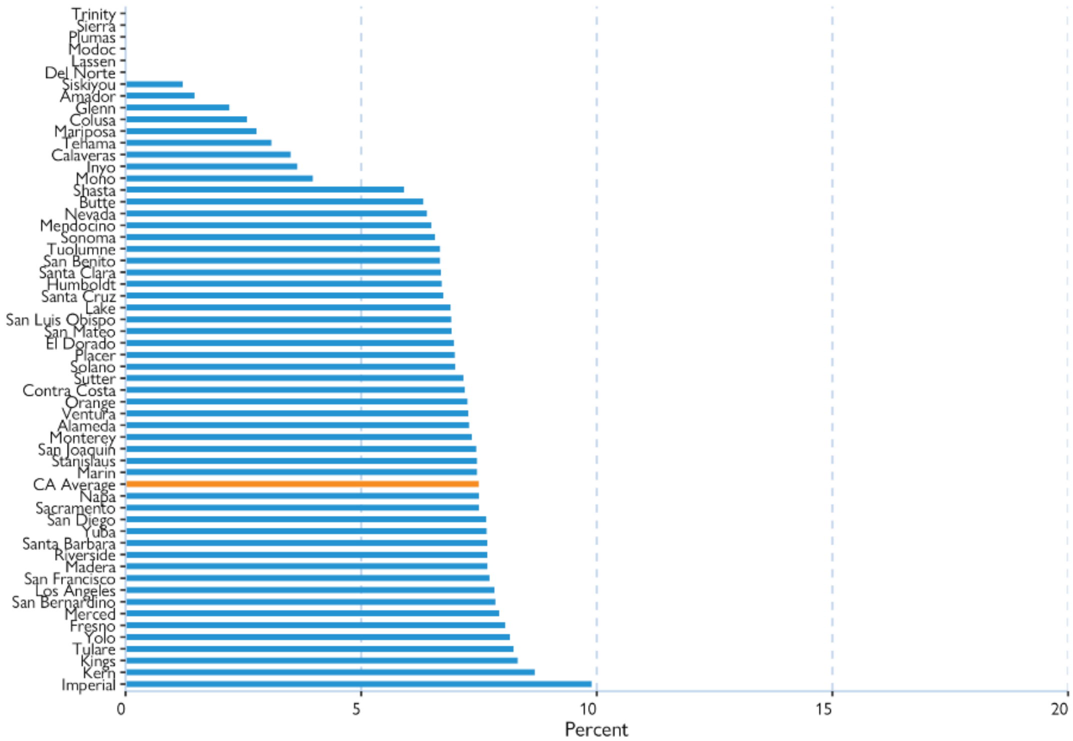
Notes: N = 79. Source = EDD. The line represents the number of claimants whose benefit year began each week and who have ever exhausted benefits divided by the total number of claimants whose benefit year began each week. Figure does not include claimants who only ever received PUA. For more information about the cohort exhaustion rate, please refer to Section 1.2 of the text.

So far, our cohort-level exhaustion rate estimates during the pandemic have been somewhat lower than what prior literature has found during past recessions, though direct comparisons are difficult because our analysis focuses on California whereas other work has estimated national averages. Nicholson & Needels (2006) look at cohort exhaustion rates during recession years between 1970 and 2003. They show that the (national) exhaustion rate for the early 2000s recession was on average 32%. In general, it is hard to predict the direction of exhaustion rates during recessions because when unemployment duration increases, the benefit duration also increases due to extension programs.

Mueller et al. (2016) estimated cohort exhaustion during the Great Recession. They show that, at the beginning of the recession, exhaustion rates decreased because of extended benefits, but eventually they started to increase because of the rise of unemployment durations. Our estimates for cohort exhaustion rates in 2020 must be interpreted with caution because as of June 2021 a vast number of claimants still had remaining benefit durations. Although our data do not extend far enough in time to measure it, the end of extension benefits in September 2021 likely increased the cohort exhaustion rates substantially for 2020 cohorts.

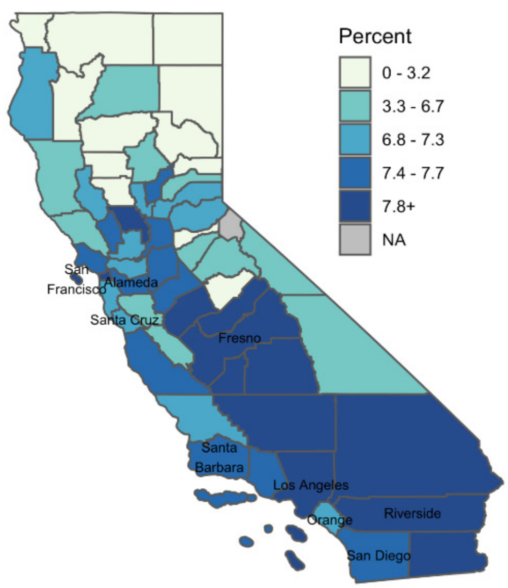
In contrast to our cross-state analysis of exhaustions as a share of continuing claimants in December of 2020 in the DOL data, when examining geographic differences in exhaustion rates within California, we analyze the cohort-specific exhaustion rates of claimants who began claiming UI in March of 2020. Figure 23 plots cohort exhaustion rates by county in California. Some of the highest rates of exhaustion among March 2020 entrants were in the counties of Imperial, Kern, and King. Figure 24 maps cohort exhaustion rates by county, and shows a pattern that a larger share of claimants in Southern California have exhausted benefits than in Northern California.

Figure 23: Exhaustion Rates Within California, County-Level Bar Graph



Notes: N = 58. Source = EDD. Each blue bar represents the Exhaustion Rate in each county for claimants whose benefit year began in March of 2020, and who exhausted by the end of Q2 2021. The orange bar represents the California average weighted by population in December 2019. For more information about the exhaustion rate, please see Section 1.2 of the text.

Figure 24: Exhaustion Rates Within California, County-Level Map

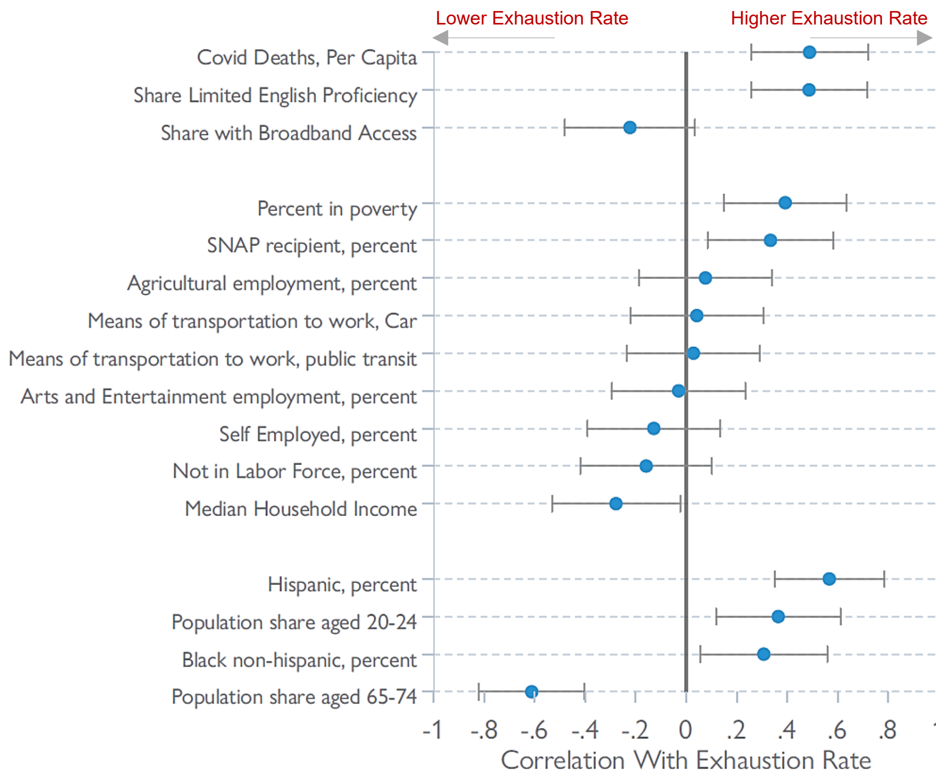


Notes: N = 58. Source = EDD. The map colors represent the exhaustion rate (in percent) from the EDD of the cohort whose benefit year began in March of 2020, and who exhausted by the end of Q2 2021. See Section 1.2 of text for full definition of exhaustion rates.

Figure 25 describes how exhaustion rates vary across counties in relation to our standard set of county-level covariates.[33] Exhaustion rates have been substantially higher in counties with more limited-English speakers, as well as those that reported more COVID-19 deaths. Poorer counties have also seen higher rates of exhaustion, as have those with higher share of Black or Hispanic residents. Interestingly, whereas states with more elderly residents had higher exhaustion rates, we find in California that counties with more elderly residents have substantially lower exhaustion rates.

Figure 26 describes how the geography of exhaustion rates in California has changed from 2019 to 2020. While a slight trend emerges that many of the magnitudes of the correlations have fallen during the pandemic, there are no statistically significant changes in the correlations along any of the dimensions studied here.

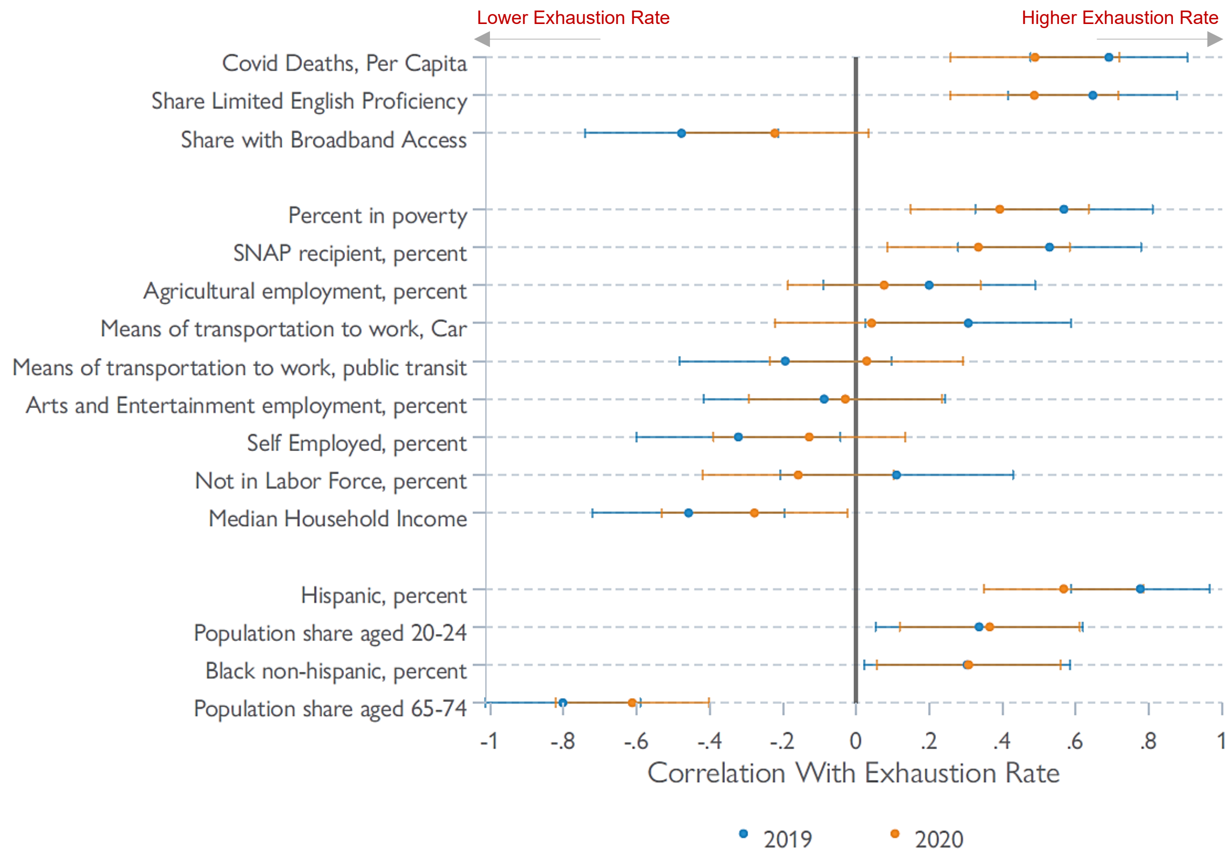
Figure 25: Exhaustion Rates Within California, County-Level Correlations



Notes: N = 58. Source = EDD and ACS. Each dot represents the correlation between the covariate and the exhaustion rate weighted by population in 2019. All variables are measured at the county level. Error bars represent the 95% confidence interval. The Exhaustion Rate is the number of claimants whose benefit year began during the weeks of 3/15/2020 or 3/22/2020 and exhausted benefits by Q2 2021, divided by the number of total claimants whose benefit year began those weeks. For more details on the exhaustion rate and the sources of the covariates, please see Section 1.2 of the text and the data appendix.

[33] All statistically significant correlations are significant at the 95% confidence level.

Figure 26: Exhaustion Rates Within California, County-Level Correlations, 2019 vs 2020



Notes: N = 58. Source = EDD and ACS. Each dot represents the correlation between the covariate and the exhaustion rate in 2020 and 2019 weighted by population in 2019. All variables are measured at the county level. Error bars represent the 95% confidence interval. The Exhaustion Rate is the number of claimants whose benefit year began in March 2020 and March 2019 and exhausted benefits by Q2 2021, divided by the number of total claimants whose benefit year began those weeks. For more details on the exhaustion rate and the sources of the covariates, please see Section 1.2 of the text and the data appendix.

3 Conclusion

In this report, we establish important new measures and facts about access to UI during the pandemic. We put forward three measures of access to UI that can be operationalized in commonly accessible datasets based around public DOL aggregated data: first payment rates, recipiency rates, and exhaustion rates. In the context of California, we have validated and explored extensions to these measures using UI claims microdata.

Several key patterns have emerged when comparing our measures of UI access during the pandemic across states and across counties within California. Across states, a clear pattern emerges that residents of states with more generous UI policies have seen higher rates of UI access during the pandemic. Though this is not a causal study, the patterns are strongly suggestive that policy has played a key role in driving disparities in access to UI across states. Demographic and socioeconomic patterns have also emerged, both across states and within California. Our metrics of access to UI have generally indicated higher access in areas with more affluent residents, more access to broadband internet, and more English-speaking residents, and less access in areas with more Black or Hispanic residents.

While these indications of place-based differences in access to UI during the pandemic are concerning, more research is needed to establish what is driving these disparities. In the remainder of this section, we outline key questions raised by this report and other gaps in knowledge, recommend new data collection efforts, and propose what DOL should fund in the future.

Questions left unanswered

Data constraints prevented the research team from pursuing additional analysis and gaining a deeper understanding on several important questions relating to UI access.

1. Although the team intended to construct recipiency rates by race and ethnicity from the DOL data, a key obstacle arose. Within the data collected by DOL on the demographics of continuing claimants, there are important differences in how states ask UI claimants about their race and ethnicity. In some states, race and (Hispanic) ethnicity are asked as separate questions, and in other states they are asked as one question. This apparent inconsistency makes comparisons of demographic data across states difficult. It also implies that race-based UI statistics cannot be easily compared to other labor market data, making it difficult to systematically compute recipiency rates by race and ethnicity.
2. A second data limitation is limited information on claimants of programs other than regular state UI. In particular, demographic information for continuing claimants is reported only for individuals claiming regular state UI, which excludes those on PEUC, EB, and PUA. This limits the scope of the analysis to the demographics of only regular UI claimants, which limits our understanding of the extent to which more vulnerable populations are being served by extension programs. For instance, our prior research (March 18th report) found that in early February 2021, 57% of Californians receiving regular UI benefits (not on extensions) had a high school degree or less. However, in that same week, more than 64% of individuals receiving benefits through the EB program had a high school degree or less, reflecting the important role of this program for these workers. In addition, first and final payments for the PUA program are not reported by DOL, which meant that the team could not report on measures of access for PUA claimants.
3. A more fundamental data constraint which shapes any analysis of access to UI using administrative data in the U.S. is that information on unemployed workers who are not currently receiving UI benefits is virtually nonexistent. The importance of this gap is most clear when considering recipiency. An individual-level measure of recipiency based on administrative data would be extremely accurate, potentially even in small areas or groups, avoiding timing problems inherent in aggregate measures of benefit receipt, measurement error problems inherent in aggregate measures of unemployment, and small-sample problems that can affect both. To construct such an individual-level administrative recipiency measure, researchers need to be able to identify unemployed workers in administrative earnings data regardless of whether they receive UI benefits

(or even file a UI claim). This is difficult to do since administrative earnings data records are quarterly, and include only the earnings amounts paid by each employer. In these data, separations to unemployment are typically indistinguishable from separations to non-employment or voluntary job switches, and the date of the separation is only measurable at the quarterly level.

4. A similar issue arises at the end of periods of insured unemployment. Without better data on transitions to/from unemployment, a researcher cannot know whether, for example, an exhaustee transitions immediately back to employment or remains unemployed for some period. Finally, even if a researcher is comfortable with this limited ability to observe uninsured unemployment spells in administrative data, they would be unable to break down such a measure by demographics, location, or many other dimensions of interestsince quarterly earnings data contains no contextual information on workers other than their employer and their earnings.

Beyond these data issues, there are several questions and analyses the current report does not pursue that could be addressed in future work with currently available data.

Among others, little is known about how UI access has changed in later stages of the pandemic, such as the summer and fall of 2021. A key question will be how UI access changed when several states terminated PEUC and PUA early in the summer of 2021. Similarly, more research will be needed to understand the impacts of the September 2021 benefits expiration. The data used in this report is also not recent enough to ascertain how vaccinations have altered access to UI as the economy has begun to reopen.

A final set of questions concerns causality. While it is useful to know that differences in access to UI exist across counties and states, the report at present does not shine light into what particular programs, policies, or practices may be causing these differences. This is a difficult question, since policies may themselves be affected by the fundamental forces helping to determine UI access. As we further outline below, additional research would be able to systematically explore how different policies contribute independently to the measures of UI access studied here using variation in UI policies across states and over time in controlled regression and difference-in-differences analyses.

Other gaps in Knowledge

Other substantial gaps in knowledge still remain, which are tougher to resolve but nonetheless important to recognize.

For our county-level analysis of UI recipiency rates, we rely on unemployment estimates provided by Local Area Unemployment Statistics (LAUS). These estimates are generated by the U.S. Bureau of Labor Statistics using a model which uses both CPS data and UI claims data. Because of this, if a county has low rates of UI claiming per person who is counted as unemployed in the CPS, this will affect the county's unemployment estimate used in the denominator of our measure. This means that counties with lower actual recipiency rates may have a smaller denominator in the recipiency rate estimate we construct, meaning this estimated recipiency rate would be biased upwards. Ideally, we could construct local measures of unemployment strictly from the CPS, however the survey sample size is insufficient to do so in a large number of counties. Exploring other ways to identify workers at risk of becoming unemployed and hence of applying for UI benefits as discussed above would be one strategy for analyzing UI access in smaller labor markets.

New Data Collection Efforts

Several new data collection efforts that DOL could readily undertake would aid in further research on access to UI during the pandemic.

In order to compare the racial and ethnic makeup of UI claimants to individuals responding to the CPS (which is often used to construct estimates of unemployment, labor force participation, and more), the questions which ask about these characteristics need to be comparable. This means that individuals should be asked the same questions in each data source, and be given the same set of possible responses. This is currently not the case. In the CPS, individuals are asked about their Hispanic ethnicity in one question, and then about their race in another. Thus they are able to identify as Hispanic and Black, not-Hispanic and Black, Hispanic and White, and so on. However, in some states, the application for UI asks about race and ethnicity in just a single question. This means that individuals may identify differently in one data source than in another — which could artificially raise or lower each group's measure of UI access. If DOL were to specify how states should ask these questions, it would greatly assist researchers aiming to shed light on racial and ethnic disparities.

As detailed above, we believe that the research on UI access in the U.S. is extremely limited by the lack of administrative, individual-level data on unemployed workers who are not currently receiving UI benefits. At a high level, an ambitious approach to solving this problem would involve collecting information on the timing and nature of both job separations and new hires. Job separation information might consist of the date on which an employee separates from an employer, and the reason for that separation (e.g., quit, fired for cause, laid off due to lack of work). New hire information might consist of simply the date that a worker first works for a given employer. This information can be collected directly from employers, and indeed the National (or State) New Hires Databases (which are currently administered by state workforce agencies but utilized primarily to collect delinquent child support payments) provide a useful example of how this might work in practice. We believe that DOL should investigate and consider strategies to incentivize state workforce agencies to add such information to their quarterly earnings data. Such efforts could be strengthened by adding additional worker demographics or other information to the quarterly earnings data, for example age, gender, or hours worked. Such data might be collected directly from employers (using the same process by which earnings data are collected) or obtained from other sources, such as other state agency datasets.

Finally, data on exhaustions is surprisingly sparse, especially given how frequently UI exhaustion limits jobless workers' access to benefits – and how correlations suggests that this more likely affects workers already vulnerable to adverse outcomes. The data supplied by DOL indicates only the number of claimants who have exhausted particular UI programs, and so it is not well-suited for research on exhaustions during periods of extensions, particularly when extension programs were abruptly modified. To aid in further research on identifying disparities in exhaustion rates, we suggest that DOL collect data on claimants who have exhausted *all* UI programs, not just particular programs. [34]

Suggestions for DOL Funding Priorities

Additional work is needed to understand the impact of the UI system's design on equity in access. To conclude this report, we have grouped our suggestions for next research priorities in this area into eight broad buckets:

1. *Studies on Methodological Insights from Individual Claims Data to Aid Interpretation of DOL-ETA Tables.* This report has demonstrated that individual-level claims data from states' UI systems can be used to meaningfully improve on the granularity and precision of measures of access. DOL should fund additional research to further refine estimates in the individual claims data. A focus of future work based on the individual claims data should also include clarifying for the public how the vast trove of publicly available DOL-ETA tables should be interpreted, particularly as long backlogs during the pandemic have called into question the accuracy of aggregate payment counts.
2. *Studies Focused on Exhaustions.* Although exhaustion is a pivotal event in the timeline of a jobless worker's access to UI, the topic has proven notoriously difficult to measure or study in DOL-ETA tables due to how data are aggregated. DOL should fund additional work in individual-level UI claims data focused on measuring exhaustion rates over time, space, and by demographics including race, ethnicity, gender, age, and education levels, among others. Individual claims data can be used to evaluate methods of estimating exhaustion rates in aggregated DOL data (Nicholson & Needels, 2006; US DOL ETA, 2021). In addition to informing policy on UI extensions, this work may also inform DOL's data collection processes in the future.
3. *Studies on the Effects of State-Level Turn Offs.* Due to recent state-level policy changes, DOL should fund additional studies to analyze how the state-level staggered timing of PEUC and PUA turn-offs have impacted access to UI across states. Comparing the magnitudes of these turn-offs to those of the Great Recession would be useful in this context.

---

[34] Reporting exhaustion counts by program also complicates the creation of easily interpretable exhaustion rates. Arguably the most useful denominator for an exhaustion rate is some group of *claims*. For example, a cohort of claimants beginning their unemployment spell in some time period, as used in our CA microdata analysis of exhaustion. If researchers are limited to counts of exhaustees (numerator in an exhaustion rate) by program, it is difficult to report an overall exhaustion rate for a group of claims. Researchers are instead limited to reporting rates such as the percentage of claimants' *payments* in some time period that are the final payments before an exhaustion. These rates complicate comparisons of exhaustion rates across groups, because such comparisons may be confounded by variation in the distribution of claim start dates in those groups. For example, imagine a researcher would like to compare exhaustion rates across states for some period of time. Suppose that in state A, all current continuing claimants had just begun their UI spell, while in state B, all claimants began their spell some months earlier. State A will have an exhaustion rate of zero, state B will not---but what we really want to know is what percentage of those current continuing claimants will *eventually* exhaust their benefits. This is not possible without complicated assumptions or counts of exhaustees across programs.

4. *Studies on the Role of PUA in Access.* DOL should fund additional research into how the PUA program has shaped access to UI during the pandemic. Research should estimate recipiency rates of PUA, with a focus on self-employed workers and wage workers not eligible for regular UI. Comparisons of the effect of the PUA program on labor supply choices would also be valuable for policy making. Because DOL does not report as much aggregate data on PUA as for other programs, individual UI claims data would be particularly valuable to such a study.
5. *Studies on the Importance of the UI Application Margin.* While this report has documented disparities in a wide range of ways that jobless workers interact with the UI system, little is known about how jobless workers' decision to file a claim has changed during the pandemic. DOL should fund future work to investigate changes in the rate at which jobless workers applied for UI by comparing DOL new initial claims counts to JOLTS separations and CPS newly unemployed workers.
6. *Studies on Policy Effects through Controlled Regressions*. Given the wealth of policy and demographic correlates assembled for this report, multivariate regression analysis would be useful to tease apart the impacts of particular policies holding others constant. For instance, a regression "horse race" framework would aid in the interpretation of which particular state-level policies are likely driving differences in access as opposed to correlated with other policies. Additional covariates could be collected for this analysis.
7. *Studies on Policy Effects through Comparisons over Time*. The present analysis is largely cross-sectional in that it compares differences in access across space. Given the vast number of state-level policy changes (e.g., such as changes in benefit levels or durations, changes in monetary and non-monetary eligibility), that have occurred during the decades for which the DOL-ETA data are available, DOL should fund additional work implementing difference-in-differences strategies that would provide policy-relevant estimates of the effects of UI policy changes on various measures of access.
8. *Studies on Race and Ethnicity in the DOL data.* To make the DOL-ETA data more useful for studying racial equity in access to UI, DOL should sponsor an effort to ascertain how states collect and report race and ethnicity data. This would allow recipiency rates by race and ethnicity to be constructed from the public DOL-ETA data. A careful effort should be undertaken to examine each state's method of soliciting race and ethnicity data prior to interpreting results, due to the high likelihood that inconsistencies may occur across states, over time, and by method of collection (e.g., paper forms, online applications, by phone, or in-person observations by caseworkers).

Acknowledgments

The California Policy Lab produced the figures and calculations through an ongoing partnership with the Labor Market Information Division of the California Employment Development Department. Any statements should only be attributed to the California Policy Lab, and do not reflect the views of the Labor Market Information Division of the California Employment Development Department. The calculations were performed solely by the California Policy Lab, and any errors or omissions are the responsibility of the California Policy Lab, not of the Labor Market Information Division of the California Employment Development Department.

For inquiries about the definitions, methodology, and findings of this policy report, please contact Till von Wachter. Email: tvwachter@econ.ucla.edu.

To obtain the data tabulations used in this report, please contact: Dr. Muhammad Akhtar, Chief, Labor Market Information Division, California Employment Development Department. Email: Muhammad.Akhtar@edd.ca.gov.

The California Policy Lab builds better lives through data-driven policy. We are an independent, nonpartisan research institute at the University of California with sites at the Berkeley and Los Angeles campuses.

This research publication reflects the views of the authors and not necessarily the views of our funders, our staff, our advisory board, the Employment Development Department, the US Department of Labor, or the Regents of the University of California.

Works Cited

Anderson, P. (2020). *Unemployment Insurance During the COVID Crisis: Lessons for Improving the UI Program*. Federal Reserve Bank of Philadelphia.

Anderson, P. M., & Meyer, B. D. (1997). Unemployment Insurance Takeup Rates and the After-Tax Value of Benefits*. *The Quarterly Journal of Economics*, *112*(3), 913–937. https://doi.org/10.1162/003355397555389

Bell, A., Hedin, T., Schnorr, G., & Von Wachter, T. (2020). *An Analysis of Unemployment Insurance Claims in California During the COVID-19 Pandemic* (California Policy Lab Policy Brief). California Policy Lab.

Bell, A., Hedin, T., Schnorr, G., & Von Wachter, T. (2021). *An Analysis of Unemployment Insurance Claims in California During the COVID-19 Pandemic* (California Policy Lab Policy Briefs). California Policy Lab. https://www.capolicylab.org/wp-content/uploads/2021/06/June-30th-Analysis-of-Unemployment-Insurance-Claims-in-California-During-the-COVID-19-Pandemic.pdf

Chetty, R. (2008). Moral Hazard versus Liquidity and Optimal Unemployment Insurance. *Journal of Political Economy*, *116*(2), 173–234.

Chetty, R., Friedman, J., Hendren, N., Stepner, M., & Team, T. O. I. (2020). *The Economic Impacts of COVID-19: Evidence from a New Public Database Built Using Private Sector Data* (No. w27431; p. w27431). National Bureau of Economic Research. https://doi.org/10.3386/w27431

Chetty, R., Hendren, N., Kline, P., & Saez, E. (2014). Where is the land of Opportunity? The Geography of Intergenerational Mobility in the United States *. *The Quarterly Journal of Economics*, *129*(4), 1553–1623. https://doi.org/10.1093/qje/qju022

Cook Political Report. (2021). *2020 National Popular Vote Tracker*. https://cookpolitical.com/2020-national-popular-vote-tracker

Department of Labor. (2020). *Comparison of State Unemployment Laws 2020*. Department of Labor. https://oui.doleta.gov/unemploy/pdf/uilawcompar/2020/complete.pdf

Edwards, K. A. (2020, July 15). *The Racial Disparity in Unemployment Benefits*. https://www.rand.org/blog/2020/07/the-racial-disparity-in-unemployment-benefits.html

Fields-White, M., Graubard, V., Rodriguez, A., Zeichner, N., & Robertson, C. (2020, September 17). *Unpacking Inequities in Unemployment Insurance*. New America. http://newamerica.org/pit/reports/unpacking-inequities-unemployment-insurance/

Ghitza, Y., & Steitz, M. (2020). *DEEP-MAPS - Model of the Labor Force*. Catalist. https://catalist.us/deep-maps/

Gould-Werth, A. (2016). Workplace Experiences and Unemployment Insurance Claims: How Personal Relationships and the Structure of Work Shape Access to Public Benefits. *Social Service Review*, *90*(2), 305–352. https://doi.org/10.1086/687298

Gould-Werth, A., & Shaefer, H. L. (2013). Do Alternative Base Periods Increase Unemployment Insurance Receipt Among Low-Educated Unemployed Workers? *Journal of Policy Analysis and Management*, *32*(4), 835–852. https://doi.org/10.1002/pam.21708

Gruber, J. (1997). The Consumption Smoothing Benefits of Unemployment Insurance. *American Economic Review*, *87*(1), 192–205.

Hellerstein, E. (2020, April 2). Non-English speakers struggle to file coronavirus unemployment claims. *CalMatters*. http://calmatters.org/california-divide/2020/04/non-english-speakers-struggle-unemployment-applications/

Landais, C., Michaillat, P., & Saez, E. (2012). *Optimal Unemployment Insurance over the Business Cycle* (NBER Working Paper No. 16526). National Bureau of Economic Research. http://ideas.repec.org/p/nbr/nberwo/16526.html

Mueller, A. I., Rothstein, J., & von Wachter, T. M. (2016). Unemployment Insurance and Disability Insurance in the Great Recession. *Journal of Labor Economics*, *34*(S1), S445–S475. https://doi.org/10.1086/683140

New York Times. (2021). *Coronavirus (Covid-19) Data in the United States*. https://github.com/nytimes/covid-19-data

Nichols, A. L., & Zeckhauser, R. J. (1982). Targeting Transfers through Restrictions on Recipients. *The American Economic Review*, *72*(2), 372–377.

Nicholson, W., & Needels, K. (2006). Unemployment Insurance: Strengthening the Relationship between Theory and Policy. *Journal of Economic Perspectives*, *20*(3), 47–70. https://doi.org/10.1257/jep.20.3.47

Pope, D. G., & Sydnor, J. R. (2010). Geographic Variation in the Gender Differences in Test Scores. *Journal of Economic Perspectives*, *24*(2), 95–108. https://doi.org/10.1257/jep.24.2.95

Schmieder, J. F., von Wachter, T., & Bender, S. (2012). The Effects of Extended Unemployment Insurance Over the Business Cycle: Evidence from Regression Discontinuity Estimates Over 20 Years *. *The Quarterly Journal of Economics*, *127*(2), 701–752. https://doi.org/10.1093/qje/qjs010

Shaefer, H. L. (2010). Identifying Key Barriers to Unemployment Insurance for Disadvantaged Workers in the United States. *Journal of Social Policy*, *39*(3), 439–460. https://doi.org/10.1017/S0047279410000218

US Bureau of Labor Statistics. (2021). *Local Area Unemployment Statistics Home Page*. https://www.bls.gov/lau/

US DOL ETA. (2021). *UI Data Summary Glossary, Employment & Training Administration (ETA)—U.S. Department of Labor*. https://oui.doleta.gov/unemploy/content/data_stats/datasum99/4thqtr/gloss.asp

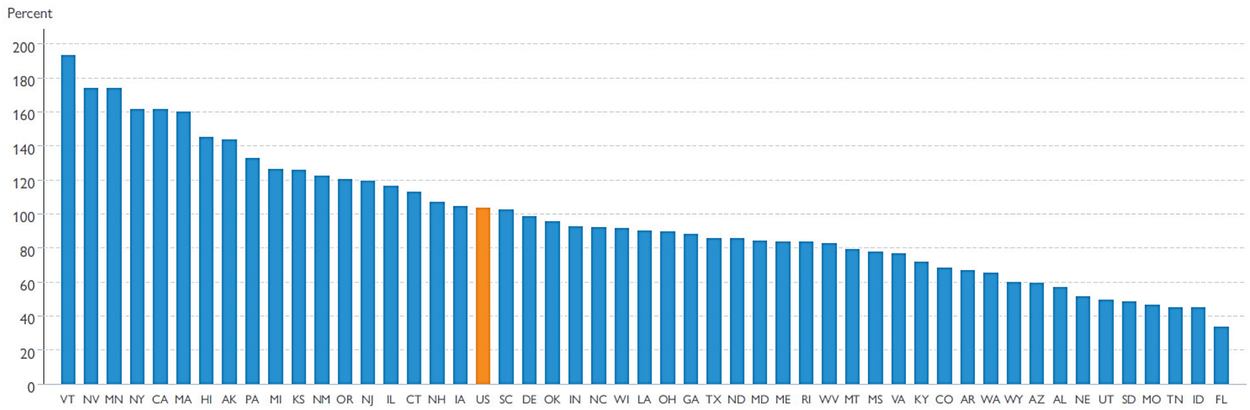
Viser, C., Camacho-Craft, I., Dutta-Gupta, I., & Grant, K. (2021). *» No Choice: The Implications of Unmet Child Care Needs For Unemployment Assistance & Paid Leave Access During The COVID-19 Pandemic* (p. 16). Georgetown Center on Poverty and Inequality.

https://www.georgetownpoverty.org/issues/state-by-state-implications-of-unmet-child-care-needs/

Wittenberg, D., Fishman, M., Stapleton, D., Scrivner, S., & Tucker, A. (1999). *Literature Review and Empirical Analysis of Unemployment Insurance Recipiency Ratios*. US Department of Labor. https://wdr.doleta.gov/research/FullText_Documents/Literature%20Review%20and%20Empirical%20Analysis%20of%20Unemployment%20Insurance%20Recipiency%20Rates.pdf

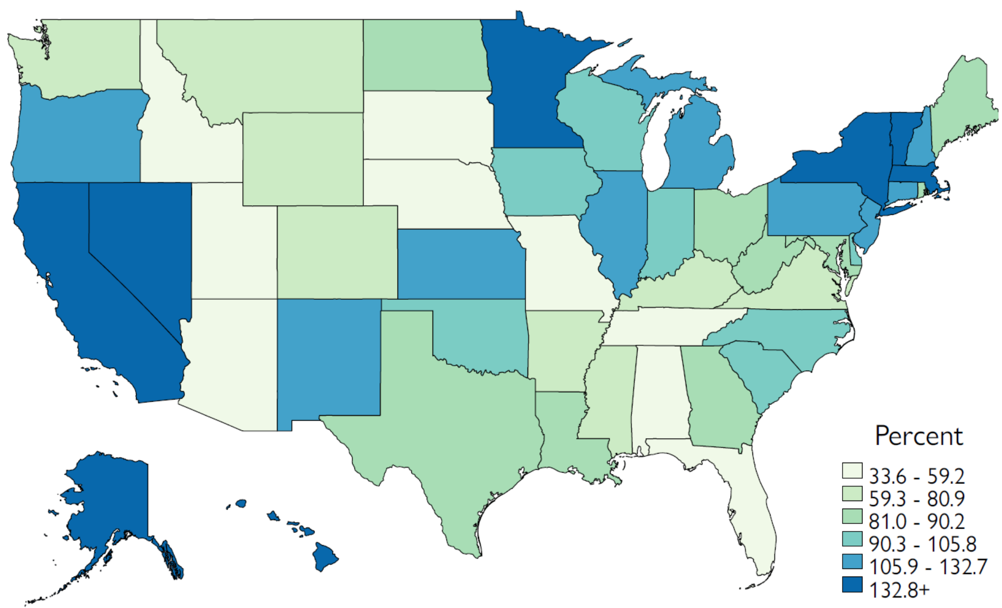
A1: Figure Appendix

Figure A1: U3 Recipiency Rates Across States, Bar Graph



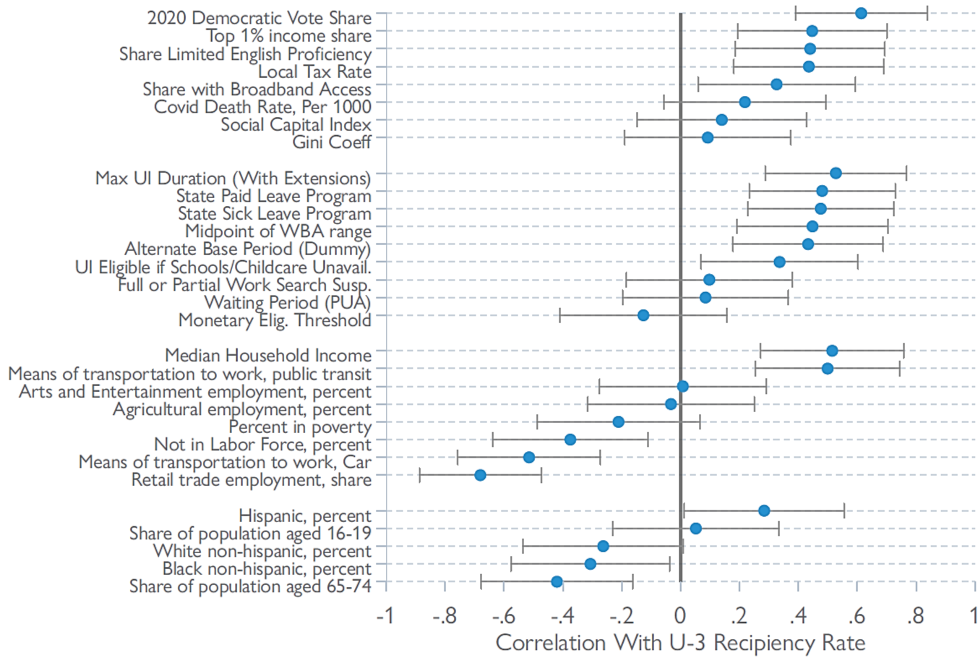
Notes: N = 50. Source = DOL. The blue bars represent the U3 recipiency rates across states for the week of December 5th, 2020. The orange bar represents the US weighted average U3 recipiency rate. The recipiency rate is the number of continuing claims paid from the DOL divided by the number of U3 Unemployed from the CPS. For more details on the recipiency rate please see Section 1.2 of the text.

Figure A2: U3 Recipiency Rates Across States, Map



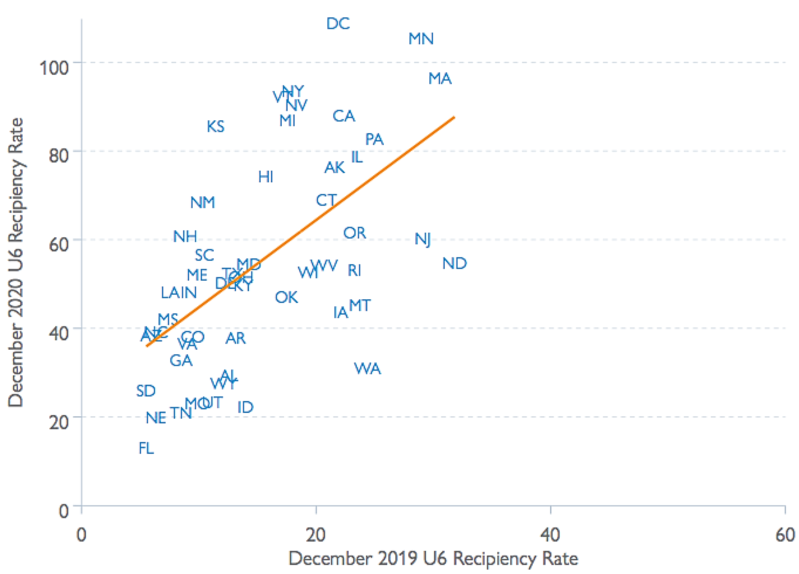
Notes: N = 50. Source = DOL. Map colors indicate the U3 recipiency rates across states for the week of December 5th, 2020. The recipiency rate is the number of continuing claims paid from the DOL divided by the number of U3 Unemployed from the CPS. For more details on the recipiency rate please see Section 1.2 of the text.

Figure A3: U3 Recipiency Rates Across States, Correlations



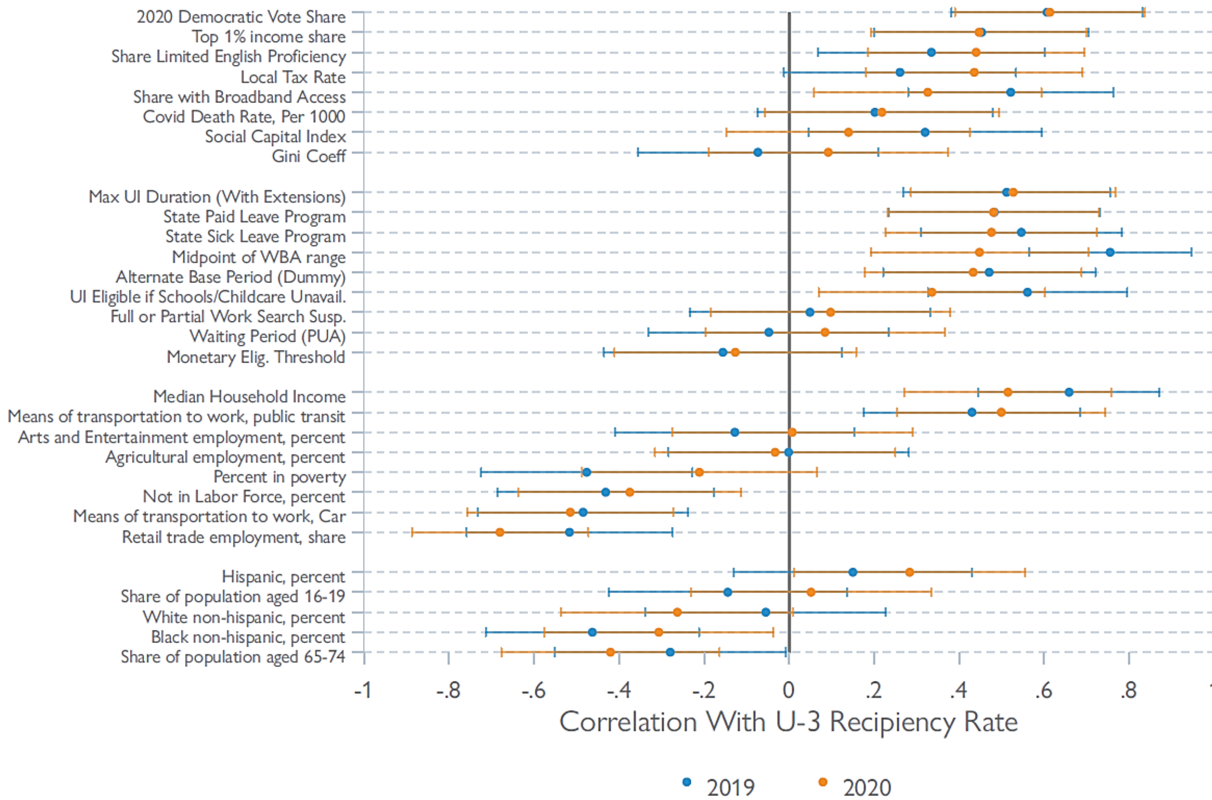
Notes: N = 50. Source = DOL and ACS. Each dot represents the correlation between the covariate and the U3 recipiency rate in December 2020 weighted by population in 2019. All variables are measured at the state level. Error bars represent the 95% confidence interval. The recipiency rate is the number of continuing claims paid from the DOL divided by the number of U3 Unemployed from the CPS. For more details on the recipiency rate and the sources of the covariates, please see Section 1.2 of the text and the data appendix.

Figure A4: Recipiency Rates Across States, Scatterplot, 2019 vs 2020



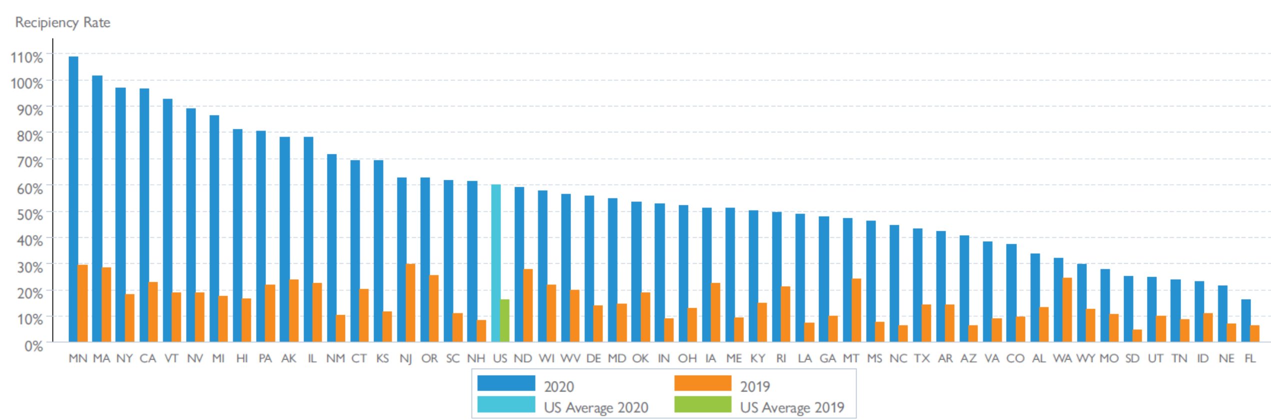
Notes: N = 50. Source = DOL. Each dot represents the recipiency rate in December 2019 and December 2020 for each state. All variables are measured at the state level. The line represents the linear best fit line. The recipiency rate is the number of continuing claims paid from the DOL divided by the number of U6 unemployed from the CPS. For more details on the recipiency rate, please see Section 1.2 of the text.

Figure A5: U3 Recipiency Rates Across States, Correlations, 2019 vs 2020



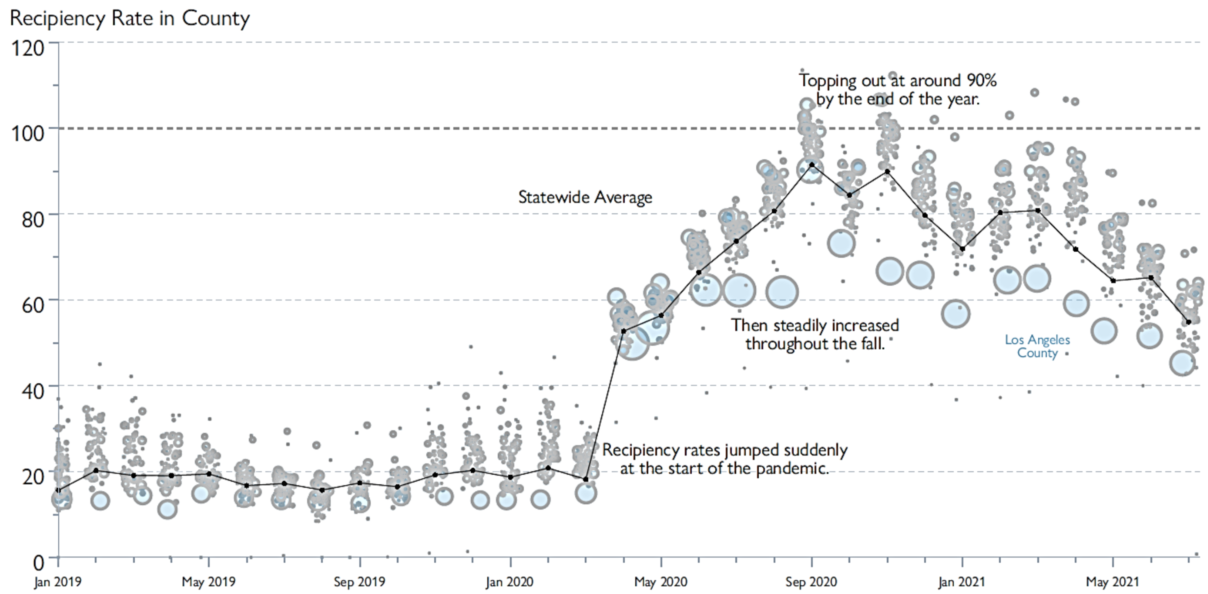
Notes: N = 50. Source = DOL. Each dot represents the correlation between the covariate and the recipiency rate in December 2019 and December 2020 weighted by population in 2019. All variables are measured at the state level. Error bars represent the 95% confidence interval. The recipiency rate is the number of continuing claims paid from the DOL divided by the number of U3 Unemployed from the CPS. For more details on the recipiency rate and the sources of the covariates, please see Section 1.2 of the text and the data appendix.

Figure A6: Recipiency Rates Across States, Bar Graph, 2019 vs 2020



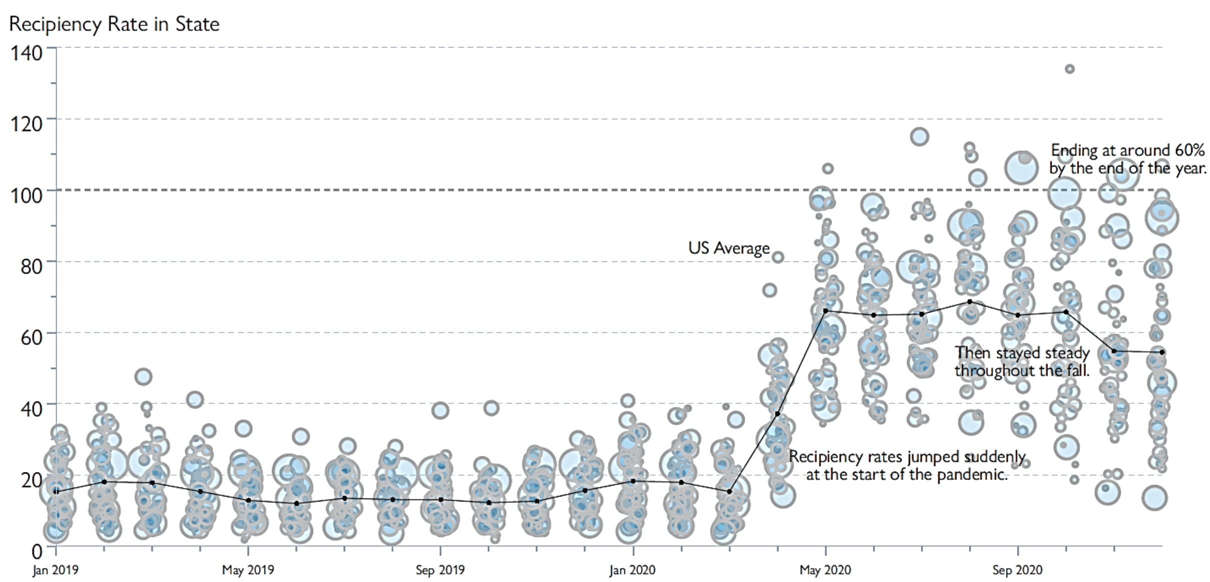
Note: N = 50. Source = DOL. The bars represent the recipiency rates across states in the first week of December for 2019 and 2020. The US average recipiency rate is weighted by population in 2019. The recipiency rate is the number of continuing claims paid from the DOL divided by the number of U3 Unemployed from the CPS. For more details on the recipiency rate, please see Section 1.2 of the text.

Figure A7: Recipiency Rates by County and Month



Note: N = 1,798. Source = EDD. Each dot represents the recipiency rate in each month for each of the 58 counties in California. The size of the dot corresponds to the number of U6 unemployed in each county. The line represents the weighted average recipiency rate in California for each month. The recipiency rate is the number of continuing claims paid from EDD divided by the number of U6 Unemployed from the CPS and LAUS. For more details on the recipiency rate, please see Section 1.2 of the text.

Figure A8: Recipiency Rates by State and Month



Notes: N = 1,200. Source = DOL. Each dot represents the recipiency rate in each month for each of the 50 US States. The size of the dot corresponds to the population in each state. The line represents the weighted average recipiency rate in the US for each month. The recipiency rate is the number of continuing claims paid from the DOL divided by the number of U3 Unemployed from the CPS. For more details on the recipiency rate, please see Section 1.2 of the text.

A2: Data Appendix

To better understand why some areas have benefited more from UI during the pandemic than others, we sourced a variety of county-level and state-level socioeconomic characteristics from public datasets. Our primary source of geographic correlates is **ACS 5-year estimate from 2014-2019**, the most recent cohort available. The ACS data spans several topics. Variables relating to the economic status of the region include median household income, percent below the Federal poverty line, percent who have broadband internet, percent who do not speak english well, and percent collecting SNAP. Measures of the region's urbanicity include population density per square mile, and median gross rent (either overall or for homes of a specific number of bedrooms). Certain information is available on transportation to work, including the amount of time spent commuting to work as well as the percent commuting via certain modes (such as car, walking, or public transit). We also collected population shares falling in particular age brackets as well as racial categories, and the percent of the labor force employed in each industry (such as food services, retail, finance, etc.). In addition, we collected information on COVID-19 cumulative infections and deaths through early December 2020 in California by county and by state in the U.S. from datasets compiled by the *New York Times* (New York Times, 2021). Finally, we collected Presidential Democratic vote share from the 2020 election for each state from *Cook Political Reports* (Cook Political Report, 2021).

We also gathered additional covariates at the state level. In particular, we obtained each state's UI policies (compiled February 2021) from the **Georgetown Center on Poverty and Inequality** (Viser et al., 2021), which includes suspension of UI work search requirements, UI eligibility given unavailable schools & child care, and waiting period for PUA (Pandemic Unemployment Assistance). Measures that reflect UI generosity of each state, like weekly UI benefit amount and maximum UI duration, were also available from GCPI, together with each state's policies on benefits other than unemployment insurance, including the availability of state paid leave programs and sick leave programs. In addition, we also gathered data (compiled January 2014) from **Opportunity Insights Data Library** (Chetty et al., 2014, 2020) on selected socioeconomic variables, including Gini coefficient (from core sample in tax records, with income topcoded at $100M in 2012 dollars), top 1% income share (computed using core sample in tax records), local tax rate (from 1992 Census of Government county-level summaries), and Social Capital Index at the CZ level, which we later converted to state level data through weighted averages by population. Finally, we extracted information on alternative base period and monetary eligibility threshold of each state from the ***2020 Comparison of State Unemployment Laws*** written by the U.S. Department of Labor (Department of Labor, 2020). We have also spot-checked this against earlier years' data collected by (Gould-Werth & Shaefer, 2013).

Summary of State and Local Variables Used in Analysis

State Variables

Metric	Definition	Variable Type	Source(s)	Construction
Recipiency Rate	The proportion of unemployed people on UI.	Continuous	Current Population Survey and Department of Labor ETA Report	The numerator is the total claimants during the first week of December from the DOL ETA reports. The denominator is the total U6 unemployed from the CPS.
First Payment Rate	The proportion of initial claims that are paid.	Continuous	Department of Labor ETA Report	The numerator is the number of first payments in a month and the denominator is the number of new initial UI claims filed in the month
Exhaustion Rate	The proportion of UI claimants that exhausted off of UI during that report week.	Continuous	Department of Labor ETA Report	The numerator is the number of final payments for the relevant program and the denominator is the total claimants from the DOL ETA reports. Before the pandemic, the numerator is equal to the final payments on base UI; during the pandemic, it is equal to final payments on PEUC.
Share with Broadband Access	Percent of households with any broadband access.	Continuous	American Community Survey	Extracted from 5-year ACS
Share Limited English Proficiency	Percent of the 5-plus population that speaks another language and speaks english less than "very well"	Continuous	American Community Survey	Extracted from 5-year ACS
Median Household Income	Median Household Income	Continuous	American Community Survey	Extracted from 5-year ACS
Percent in Poverty	Percent of families with income below the federal poverty level	Continuous	American Community Survey	Extracted from 5-year ACS

Metric	Definition	Variable Type	Source(s)	Construction
Not in Labor Force, percent	Percent of the population 16+ not in the labor force	Continuous	American Community Survey	Extracted from 5-year ACS
Means of transportation to work, public transit	The share of workers age 16+ who take public transit to work	Continuous	American Community Survey	Extracted from 5-year ACS
Means of transportation to work, car	The share of workers age 16+ who drive to work	Continuous	American Community Survey	Extracted from 5-year ACS
Agricultural Employment, percent	The share of workers age 16+ who work in agriculture	Continuous	American Community Survey	Extracted from 5-year ACS
Arts and Entertainment employment, percent	The share of workers age 16+ who work in arts and entertainment	Continuous	American Community Survey	Extracted from 5-year ACS
Retail Trade employment, percent	The share of workers age 16+ who work in retail	Continuous	American Community Survey	Extracted from 5-year ACS
Population share aged 65-74	Share of the population between 65-74	Continuous	American Community Survey	Extracted from 5-year ACS
Population share aged 16-19	Share of the population between 16-19	Continuous	American Community Survey	Extracted from 5-year ACS
Black, non-hispanic, percent	Share of the population that identifies as non-hispanic Black	Continuous	American Community Survey	Extracted from 5-year ACS
Hispanic, percent	Share of the population of any race that identifies as Hispanic	Continuous	American Community Survey	Extracted from 5-year ACS
White non-hispanic, percent	Share of the population that identifies as non-hispanic White	Continuous	American Community Survey	Extracted from 5-year ACS

Metric	Definition	Variable Type	Source(s)	Construction
2020 Democratic Vote Share	Percent of votes for Joe Biden in the 2020 Presidential election.	Continuous	Cook Political Report	Downloaded from website
Top 1% Income Share	The fraction of income within a CZ going to the top 1% defined within the CZ, computed using parents of children in Tax Records, Core Sample	Continuous	Opportunity Insights Data Library	Downloaded from website
Local Tax Rate	Total tax revenue per capita divided by mean household income per capita for working age adults (in 2000)	Continuous	Opportunity Insights Data Library	Downloaded from website
Covid Death Rate, per 1000	Confirmed COVID-19 deaths per 1,000 people, seven day moving average	Continuous	New York Times, American Community Survey	The numerator is the number of COVID-19 deaths in each state and the denominator is the population in each county from the ACS.
Social Capital Index	Standardized index combining measures of voter turnout rates, the fraction of people who return their census forms, and measures of participation in community organizations	Continuous	Opportunity Insights Data Library	Downloaded from website
Gini Coefficient	Gini coefficient computed using parents of children in the core sample, with income topcoded at $100 million in 2012 dollars	Continuous	Opportunity Insights Data Library	Downloaded from website
Max UI Duration (With Extensions)	The number of weeks of regular UI each state provides including state-funded extensions	Continuous	Georgetown Center on Poverty and Inequality (Viser et al. 2021)	Downloaded excel file

Metric	Definition	Variable Type	Source(s)	Construction
State Sick Leave Program	Does the state have any requirements for employers to provide paid sick leave	Binary	Georgetown Center on Poverty and Inequality (Viser et al. 2021)	Downloaded excel file
State Paid Leave Program	Does the state have any requirement that employers provide paid family leave or does the state fund family leave	Binary	Georgetown Center on Poverty and Inequality (Viser et al. 2021)	Downloaded excel file
Alternate Base Period (Dummy)	Does the state allow the use of an alternate base period to calculate quarterly wages for monetary eligibility	Binary	*2020 Comparison of State Unemployment Laws* by United States Department of Labor	Downloaded from website
Midpoint of WBA range	The midpoint of the states maximum and minimum weekly benefit amounts	Continuous	Georgetown Center on Poverty and Inequality (Viser et al. 2021)	Downloaded excel file
UI Eligible if Schools/Childc are Unavailable	UI eligibility if schools & child care are unavailable, by state	Binary	Georgetown Center on Poverty and Inequality (Viser et al. 2021)	Downloaded excel file
Full or Partial Work Search Suspension	To what extent do states suspend UI work search requirements	Binary	Georgetown Center on Poverty and Inequality (Viser et al. 2021)	Downloaded excel file
Waiting Period (PUA)	Waiting period for Pandemic Unemployment Assistance, by state	Binary	Georgetown Center on Poverty and Inequality (Viser et al. 2021)	Downloaded excel file
Monetary Eligibility Threshold	The minimum amount of earnings a individual must have during the base period to qualify for UI benefits	Continuous	*2020 Comparison of State Unemployment Laws* by United States Department of Labor	If the state provided two different methods for determining monetary eligibility, then we used the lower value of the two.

County Variables

Metric	Definition	Type	Source(s)	Construction
Recipiency Rate	Percent of unemployed workers who were paid UI benefits in a week in a county	Continuous	California EDD, Current Population Survey, Local Area Unemployment Statistics	The numerator is the number of claims paid each week geocoded by county from California EDD. The denominator was constructed in two steps. First using the Current Population Survey, the ratio of U3 unemployed workers to U6 unemployed workers was created for the state of California. Then the number of U3 unemployed workers by county was extracted from the Local Area Unemployment Statistics and scaled up to U6 using the state U3 to U6 ratio.
First Payment Rate	The percentage of people who claimed UI and were subsequently issued at least one payment	Continuous	California EDD	The denominator is all the people who submitted a UI claim from EDD. The numerator is the number of those people who received at least one payment. The claimants were geocoded by county.
Exhaustion Rate	The percentage of claimants who received all the UI benefits they were eligible for	Continuous	California EDD	The numerator is the number of claimants in each entry cohort who have a last payment flag and who have not received another payment in four weeks. The denominator is every claimant in the entry cohort.
Share with Broadband Access	Percent of households with any broadband access.	Continuous	American Community Survey	Extracted from the 5-year ACS by county
Share Limited English Proficiency	Percent of the 5-plus population that speaks another language and speaks english less than "very well"	Continuous	American Community Survey	Extracted from the 5-year ACS by county
Covid Deaths, Per capita	Cumulative COVID-19 deaths per capita as of December 5, 2020	Continuous	New York Times, American Community Survey	The numerator is the number of COVID-19 deaths in each county and the denominator is the population in each county from the ACS.

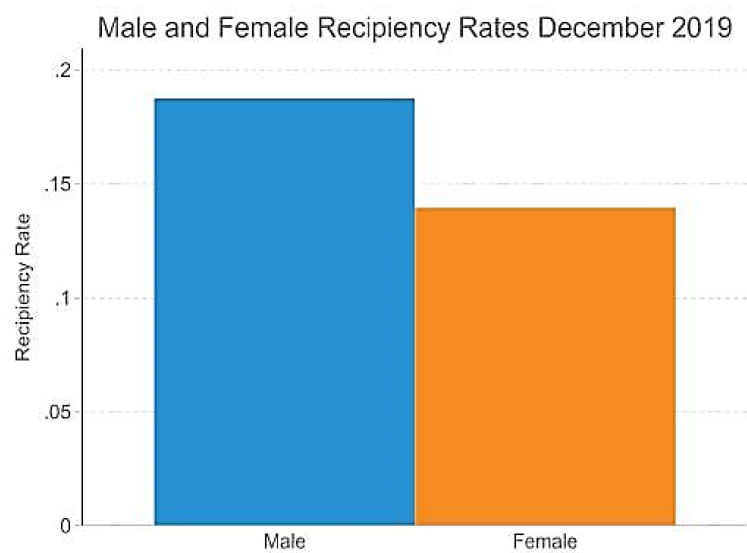
Metric	Definition	Type	Source(s)	Construction
Median Household Income	Median Household Income	Continuous	American Community Survey	Extracted from the 5-year ACS by county
Means of transportation to work, public transit	The share of workers age 16+ who take public transit to work	Continuous	American Community Survey	Extracted from the 5-year ACS by county
Means of transportation to work, car	The share of workers age 16+ who drive to work	Continuous	American Community Survey	Extracted from the 5-year ACS by county
Agricultural Employment, percent	The share of workers age 16+ who work in agriculture	Continuous	American Community Survey	Extracted from the 5-year ACS by county
Arts and Entertainment employment, percent	The share of workers age 16+ who work in arts and entertainment	Continuous	American Community Survey	Extracted from the 5-year ACS by county
SNAP recipient, percent	Percent of households that receive SNAP benefits	Continuous	American Community Survey	Extracted from the 5-year ACS by county
Self Employed, percent	The share of workers age 16+ who are self employed	Continuous	American Community Survey	Extracted from the 5-year ACS by county
Percent in Poverty	Percent of families with income below the federal poverty level	Continuous	American Community Survey	Extracted from the 5-year ACS by county
Population share aged 65-74	Share of the population between 65-74	Continuous	American Community Survey	Extracted from the 5-year ACS by county
Population share aged 20-24	Share of the population between 20-24	Continuous	American Community Survey	Extracted from the 5-year ACS by county

Metric	Definition	Type	Source(s)	Construction
Black, non-hispanic, percent	Share of the population that identifies as non-hispanic Black	Continuous	American Community Survey	Extracted from the 5-year ACS by county
Hispanic, percent	Share of the population of any race that identifies as Hispanic	Continuous	American Community Survey	Extracted from the 5-year ACS by county

A3: Demographic Differences in Recipiency Rates

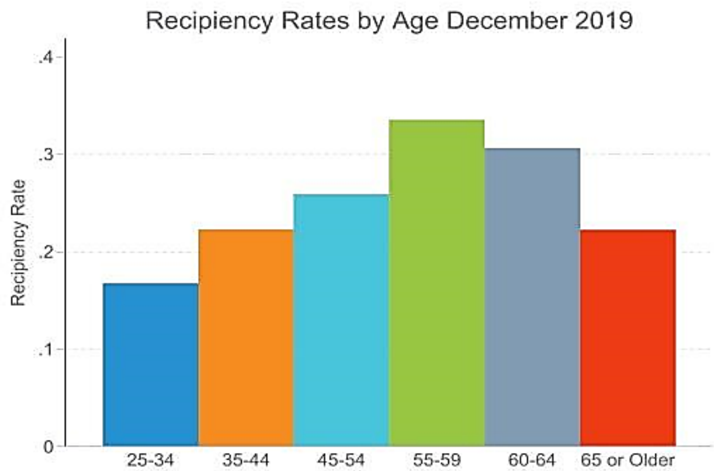
The DOL dataset includes information on the number of claimants by age and gender, and the CPS similarly allows one to measure unemployment by these variables. We are therefore able to combine these two datasets to analyze how recipiency rates, defined as the proportion of the unemployed that is on unemployment insurance, varies by these groups. The DOL claimant data does not contain this information for unemployment insurance extensions, so our analysis must be limited to before the beginning of the pandemic-related extensions that began in March of 2020.

Nationally, some clear differences exist between these demographic groups. Overall, recipiency rates for men tend to be slightly higher than for women, with unemployed men on average in December of 2019 having an 18.73% chance of being on UI compared to 13.94% of unemployed women.[35] Older unemployed workers tended to have much higher recipiency rates. Those aged 25 to 34 had an average recipiency rate of 16.74%, while those aged 55 to 59 were more than double at 33.51%. This information is visualized in the bar graphs below.



Notes: N = 50. Source = DOL. The blue and orange bars represent the recipiency rates across gender for the week of December 5th, 2019. The recipiency rate is the number of continuing claims paid from the DOL divided by the number of U6 unemployed from the CPS. For more details on the recipiency rate, please refer to Section 1.2 of the text.

[35] All national averages for all groups are a population-weighted average across the 50 states.



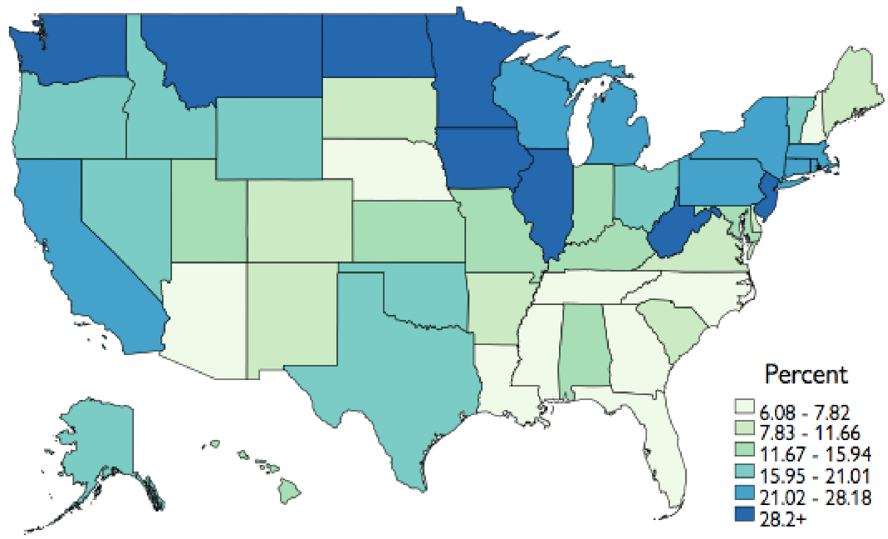
Notes: N = 50. Source = DOL. The bars represent the recipiency rates across age groups for the week of December 5th, 2019. The recipiency rate is the number of continuing claims paid from the DOL divided by the number of U6 unemployed from the CPS. For more details on the recipiency rate, please refer to Section 1.2 of the text.

These demographic differences can also be analyzed geographically. The below maps display the male and female recipiency rates as well as the recipiency rates by certain age groups per state in December of 2019. These initial results can suggest some interesting regional patterns in these recipiency rates, and several hypotheses can be explored that may explain why these geographic differences occur.[36] Due to inconsistencies in how different states ask claimants about their race, our analysis was not able to include an examination of race.

---

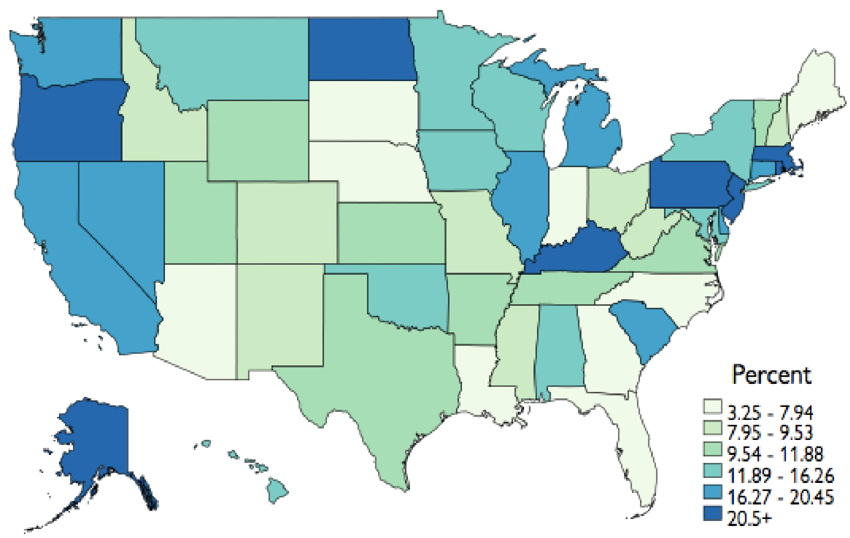
[36]Preliminary cross-state comparisons of demographic-specific recipiency rates have suggested that the analysis may be noisy due to small sample sizes in state-by-demographic cells in the CPS. Future analysis of these patterns will need to address the role of noise in this analysis. Hypotheses that could be tested include the extent to which gender differences in recipiency rates are due to cultural attitudes – such as the gender stereotype adherence index put forward by (Pope & Sydnor, 2010) – as well as the role of alternative base period policies in increasing recipiency rates among younger workers, who may have less work history.

Male Recipiency Rate, Dec 2019

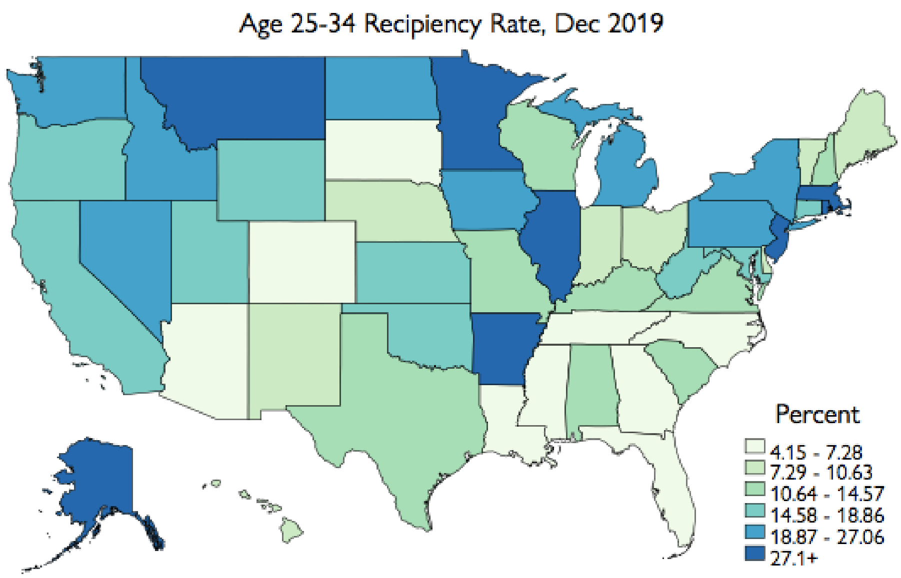


Notes: N = 50. Source = DOL. The colors represent the recipiency rates (in percent) across states for the week of December 5th, 2020 for males. The recipiency rate is the number of continuing claims paid from the DOL divided by the number of U6 unemployed from the CPS. For more details on the recipiency rate, please refer to Section 1.2 of the text.

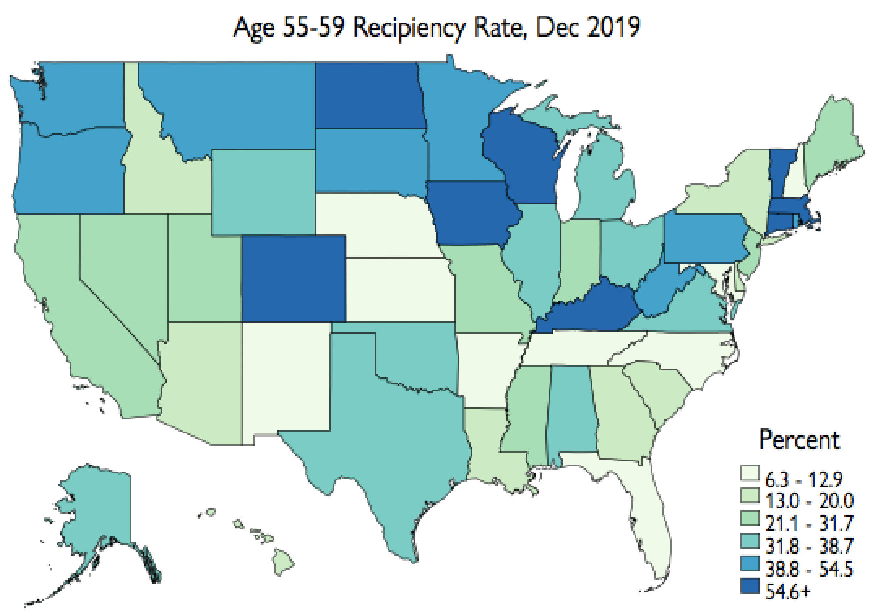
Female Recipiency Rate, Dec 2019



Notes: N = 50. Source = DOL. The colors represent the recipiency rates (in percent) across states for the week of December 5th, 2020 for females. The recipiency rate is the number of continuing claims paid from the DOL divided by the number of U6 unemployed from the CPS. For more details on the recipiency rate, please refer to Section 1.2 of the text.



Notes: N = 50. Source = DOL. The colors represent the recipiency rates (in percent) across states for the week of December 5th, 2020 for 25-34 year olds. The recipiency rate is the number of continuing claims paid from the DOL divided by the number of U6 unemployed from the CPS. For more details on the recipiency rate, please refer to Section 1.2 of the text.



Notes: N = 50. Source = DOL. The colors represent the recipiency rates (in percent) across states for the week of December 5th, 2020 for 55-59 year olds. The recipiency rate is the number of continuing claims paid from the DOL divided by the number of U6 unemployed from the CPS. For more details on the recipiency rate, please refer to Section 1.2 of the text.

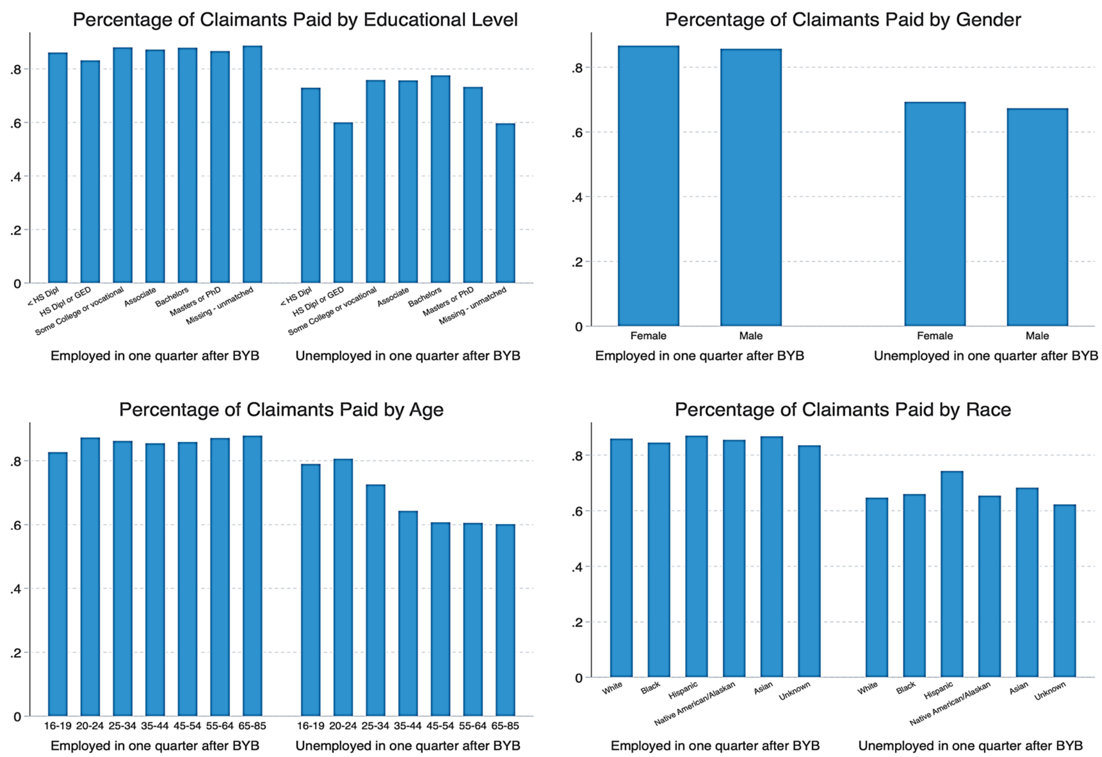
A4: Demographic Differences in First Payment Rates

Failure in receiving the first UI payment after unemployment is a challenge for consumption smoothing (Chetty, 2008; Gruber, 1997; Landais et al., 2012). This is a greater challenge if the unemployed worker is unable to find a job for extended periods. To further investigate the case, we expanded the first payment measurement within-California to be conditional on employment status after filing the UI claim, and we also derived the first payment rates for various demographics to check for potential unevenness.

The employment status one quarter after the beginning of the benefit year (BYB) of UI claimants is based on the UI Base Wage data, which includes quarterly information on wages and employer firms for UI-covered employees. We follow the employment status of the claimants with new initial claims in the second quarter of 2020 into the third quarter of 2020.

A close look at all of the figures of demographic categories shows that claimants who remained unemployed one quarter after establishing their claim are less likely to be paid. Claimants with insufficient earning history have poorer connections with the labor market. They are less likely to be paid UI benefits, and at the same time, less likely to find a job in the middle of a recession.

Focusing on the heterogeneity of first payment rates within employment status, we do not observe substantial disparities among claimants who are employed one quarter after BYB. However, differences within unemployed claimants one quarter after BYB are more outstanding. Particularly, we see that a larger share of younger unemployed claimants receive the first payment compared to older workers. This result is unexpected because even among unemployed claimants, we expected a larger share of older claimants to receive the first payment due to stronger work history. Understanding these disparities is potential future research.



Notes: N = 58. Source = EDD. The bars represent the first payment rate within California for each demographic and employment group. The first payment rate is the number of first claim payments divided by the number of new initial claims. For more details on the first payment rate, please see Section 1.2 of the text.