TECHNICAL APPENDIX

December 21, 2020

An Analysis of Unemployment Insurance Claims in California During the COVID-19 Pandemic

ALEX BELL, THOMAS J. HEDIN, GEOFFREY SCHNORR, and **TILL VON WACHTER**

SUMMARY

This Technical Appendix provides additional information about the data sources used in the extended geographic analysis of our December UI report.

Additional Data Documentation

Geocoded Samples of UI Continuing Claims from 2020

To count the number of UI recipients in a neighborhood, we use administrative program records from the Labor Market Information Division (LMID) at the California Employment Development Department (EDD). Our continuing claims analysis sample includes every payment made on each claim and every payment denied due to excessive earnings in the relevant week. The timespan of the sample for the recipiency rates analysis is all payments from January 1, 2020, to August 22, 2020. (For the more-recent recovery analysis, we supplement with geocoded claims from the week ending October 31, 2020.) For each payment or denial, we observe the date on which the payment was processed, the week of unemployment that the payment was for, the amount of the payment, and any self-reported earnings received by the claimant during the week of unemployment.

Our continuing claims sample was constructed to line up with how the Current Population Survey (CPS) defines and measures unemployment. First, we have excluded individuals who reported some earnings in the given week. This can happen, for instance, when a UI claimant is recalled to a previous employer or finds some alternative or temporary work. In such cases, CPS would not classify this individual as unemployed. We therefore drop individuals who reported some earnings during certification or had their claim denied to due to excess earnings. These two categories combined constitute approximately 20% of our continuing claims sample each week.

To better line up with the timing of CPS estimates, we count individuals by the week in which unemployment was experienced, not when it was reported or when the claim was paid. Although this method has the benefit of accuracy, it introduces potential time-censoring in that not all claims for unemployment in a particular week may have been filed yet. For this reason, we do not attempt to measure the number of claimants for weeks very near the end of our sample. In addition, we limit our recipiency rates analysis of the weekly EDD data to weeks in which the CPS was conducted, which is only once per month and typically includes the 12th of each month.

We assign Census tracts to continuing UI claims based on the address reported on the corresponding initial claim. We successfully assigned exact geocodes to approximately 90% of all initial claims for the relevant time period. The vast majority of the remaining 10% matched to a ZIP code but not a Census tract, and we do not attempt to use that data for spatial analysis. Visual inspection suggests most of the records that failed to geocode were either missing a valid address or supplied a PO box, which prevents us from mapping the record to a Census tract. Our rate of successful geocoding is slightly lower among the continuing claims sample because initial claims that did not successfully geocode were likely to have received more weeks of payments. We did not detect substantial selection along demographic lines into geocoding match status. Although our data has precise latitude and longitude of the claim, we chose Census tracts as the unit of geographic analysis because they broadly correspond to what might be considered a "neighborhood." There are approximately 8,000 Census tracts in California.

Unemployment Estimates

A key barrier to analyzing geographic differences in recipiency rates during the pandemic is that the government does not publish unemployment estimates at fine-grained geographies in real time. This is primarily a limitation of sample size. The CPS samples only about 60,000 households per month nationally, which is fewer households than there are Census tracts in the US. The most recent government statistics available on unemployment at the tract level would be averages of 2013-2018 unemployment published by the American Community Survey (ACS), which would not be useful in understanding the geographic implication of the COVID-19 pandemic.

To overcome the difficulties of measuring neighborhood-level unemployment during the pandemic, we use tract-level imputations constructed by Ghitza & Steitz (2020). While far from perfect, these estimates constitute a current best-guess – given the full set of publicly available government data – at monthly unemployment in the neighborhoods that we study. They are constructed by comparing recent CPS estimates, which are available at monthly frequencies during the pandemic at higher levels of geographic aggregation, with a variety of rich tract-level information. For example, CPS reports estimates of the number of unemployed individuals overall in a state and separately in the food services industry for recent months. Because previous surveys are informative of which Census tracts contain more food service workers, the monthly CPS releases can be modeled to shed light on which tracts one might therefore expect to have more unemployed people, based on the huge increase in unemployment among food service workers brought on by the pandemic. The models used by the authors to create the estimates used in this report make use of a great many other tract-level features, including demographics, historical unemployment, labor force participation, industry/occupation trends.

Other Geographic Correlates

To better understand why some neighborhoods have benefited more from UI during the pandemic than others, we sourced a variety of tract-level socioeconomic characteristics from public datasets. Our primary source of geographic correlates is ACS 5-year estimate from 2013-2018, the most recent cohort available. The ACS data spans several topics. Variables relating to the economic status of the neighborhood include median household income, percent below the Federal poverty line, and percent collecting SNAP. Measures of the neighborhood'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 infections and deaths (as of the end of August) in California by county from a database compiled by the *Los Angeles Times.*

References Cited in the Geographic Analysis

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.

Blank, R. M., & Card, D. E. (1991). Recent Trends in Insured and Uninsured Unemployment: Is There an Explanation? *The Quarterly Journal of Economics*, *106*(4), 1157–1189. https://doi.org/10.2307/2937960

Chetty, R., Friedman, J. N., Hendren, N., & Stepner, M. (2020). *How Did COVID-19 and Stabilization Policies Affect Spending and Employment? A New Real-Time Economic Tracker Based on Private Sector Data*. 84.

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

Ghitza, Y., & Steitz, M. (2020). *DEEP-MAPS Model of the Labor Force*. https://github.com/Catalist-LLC/unemployment/blob/master/deep_maps_20200804.pdf

McCall, B. P. (1995). The Impact of Unemployment Insurance Benefit Levels on Recipiency. *Journal of Business & Economic Statistics*, *13*(2), 189–198. https://doi.org/10.1080/07350015.1995.10524593