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MAPPING THE AMERICAN RESCUE PLAN

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Abstract
The American Rescue Plan (ARP) Act, enacted as part of the fiscal response to the COVID-19 pandemic, was the second largest federal stimulus package on record. Because the ARP provided funding to overlapping state and local entities and through various allocation formulas, the geographic distribution of the ARP's funds is complicated and not yet unraveled. In this paper, we document the geographic distribution of the ARP's funds. Compiling data on 31 ARP programs totaling $1.15 trillion and mapping that funding to the county-level, we find significant variation in the allocations not visible at the state level. The ARP sent more funds per capita to counties in low-population states, with higher levels of poverty, with a majority-minority population, and that experienced greater increases in their unemployment rates. Additionally, we identify which programs led to the differences in the funds per capita between counties, concluding that allocating funds to food assistance for needy households, SNAP and Pandemic EBT simultaneously, targeted economic need and labor market slack.

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1. Introduction

In response to the COVID-19 pandemic, the federal government provided the largest fiscal stimulus in American history. In 2020, Congress passed the $2.2 trillion CARES Act (March 2020) and the $0.9 trillion Coronavirus Response and Consolidated Appropriations Act (December 2020).[1] The initial U.S. response was especially outsize compared to other advanced economies (Romer 2021). Despite the dramatic increase in federal spending in 2020 (Figure 1), concerns about the economy's performance remained into early 2021. In January 2021, at 6.3 percent, the unemployment rate was nearly double its pre-pandemic level, with 9.9 million fewer jobs than before the pandemic and 4.3 million fewer people in the labor force.[2] Similarly, in the first quarter of 2021, economic output remained 2.5 percent below its pre-pandemic level from the fourth quarter of 2019, furthering debate over whether the U.S. economy would experience a sharp improvement in economic outcomes, or a V-shaped recovery, after the pandemic recession or something more lackluster (e.g., Gregory et al., 2020).[3]

Against this backdrop, Congress passed the $1.9 trillion American Rescue Plan (ARP) Act in March 2021. The package distributed $1,400-per-person stimulus checks, expanded unemployment benefits and tax credits, and provided grants to, among others, state and local governments, school districts, colleges, restaurants, businesses, renters, and homeowners. The ARP was the second-largest fiscal stimulus package in U.S. history, following the CARES Act one year earlier. Following the passage of the ARP, federal spending exceeded 25 percent of gross domestic product (GDP) for the second year in a row, keeping federal spending as a share

[1] For CARES, see https://apnews.com/article/donald-trump-financial-markets-ap-top-news-bills-virus-outbreak-2099a53bb8adf2def7ee7329ea322f9d; for Consolidated Appropriations Act, see https://www.politico.com/news/2020/12/20/details-stimulus-package-omnibus-bill-449499; for ARP, see https://www.cbo.gov/publication/57056.
[2] https://www.bls.gov/news.release/archives/empsit_02052021.pdf.
[3] https://www.bea.gov/sites/default/files/2021-01/gdp4q20_adv.pdf.

of economic output at its highest level since the Second World War (Figure 1).[4] In dollar terms, after adjusting for inflation, the ARP was 89 percent larger than the 2009 American Recovery and Reinvestment Act (ARRA). Even looking as far back as the Great Depression, new federal spending through the New Deal from 1933 to 1936 only lifted federal outlays as a share of GDP by 2 percentage points.

Figure 1: Federal Government Outlays as a Percent of GDP

Note: FRED series FYONGDA188S, based on OMB data. Vertical shading indicates recessions as defined by the NBER's Business Cycle Dating Committee.

We seek to determine the amount of ARP funding provided to each county and map the geographic distribution of ARP funds. Despite the magnitude of funds distributed through the ARP, its programs and allocation formulas remain understudied. This may in large part reflect

[4] Decomposing the pandemic-induced increase in federal outlays spending reveals that the increase reflects a meteoric rise in outlays for unemployment compensation ($472 billion in 2020 and $391 billion in 2021), other commerce and housing credits ($572 billion in 2020 and $315 billion in 2021), and newly-designated coronavirus payments and tax credits ($275 billion in 2020 and $580 billion in 2021), as well as outlays for health and community and regional development, which grew by 211 percent and 170 percent, respectively, in 2020 and remained in 2021 above their 2019 levels.

the complex nature in which funds were assigned. The relief package provided funds to various overlapping state and local entities, as well as specific geographies (i.e., cities, school districts, and universities) that do not necessarily correspond one-to-one with the geographic partitions at which the Census Bureau reports various demographic and economic statistics. Given these overlaps and imperfect alignments, the amount of stimulus dollars allocated to each individual community is neither readily available nor ex ante obvious.

To map the geographic distribution of ARP funds, we compile data on 31 ARP programs totaling $1.15 trillion and partition such funds down to the county level. A key advantage of our bottom-up approach is that we are able to study the geographic distribution of ARP funds not just overall, but for each individual program. The ARP contained a multitude of different spending initiatives that targeted distinct but, in some cases, overlapping populations with the goal of advancing distinct but overlapping policy goals. For example, the Emergency Rental Assistance (ERA) program targeted lower-income renters who were behind on their rents, while the Economic Impact Payments (EIPs) provided stimulus directly to taxpayers whose incomes fell below a certain level. Many households would be eligible for both ERA and EIP, but the two programs had separate goals; the former provided aid to maintain stable housing, and the latter increased household income.

Our analysis reveals significant variation across counties in ARP dollars received per capita that would not be visible at the state level, demonstrating the value added from this granular county-level analysis. We identify four key patterns of variation: counties in small-population states, high-poverty counties, majority-minority counties, and counties that experienced increased unemployment rates all received on average more funds per capita. Notably, majority-minority counties received more ARP dollars per capita even when comparing counties with similar poverty rates. We identify which of the 31 programs fueled these patterns and discuss the relevant design aspects of each.

In studying the geographic distribution of ARP dollars, we focus on the distribution of ARP funds *as allocated* by Congress. More specifically, we attempt to distribute the ARP funds under each program to each county based on the population within each county that could have potentially benefited from the funding. In doing so, we abstract from the actual spending decision of ARP grant recipients (e.g., state and local governments, school districts) primarily because data on the geographic locations of actual spending do not exist for all programs.[5] Abstracting from actual spending allows us to examine the minimum amount of stimulus ARP provided to different areas and document which programs were most or least likely to provide stimulus to economically needy areas. Moreover, better understanding the ARP and its allocations may offer a blueprint for designing future fiscal stimulus, in that our analysis may provide valuable insight into the tradeoffs between funding some programs over others.[6]

Much of the existing literature on the ARP postulates as to what impact ARP spending or particular programs within the ARP *would have* on economic outcomes. Forecasts suggested that the ARP would reduce child poverty by more than one-half in 2021 (Parolin et al. 2021). Other analyses suggested that the ARP would temporarily raise the vacancy-to-unemployment ratio thereby resulting in an increase in core inflation of about 0.3 percentage points through 2022 (Barnichon et al. 2021). Others postulate that the rental assistance provided by the ARP would

[5] Many ARP programs were not required to collect the precise geographic location of ARP spending because it would have been impractical to do so. Moreover, requiring that precise geographic location be reported by the funding recipients, e.g., state and local governments, would have substantially increased the administrative burden of administering the programs and likely would have resulted in many inaccurate submissions of the geographic locations of spending.

[6] We note here that an expansive stimulus spending package that targets policy goals beyond economic recovery may crowd out other important federal investments by increasing debt and inviting opposition to future fiscal spending (Romer 2021).

reduce evictions and homelessness through its housing support programs (Center on Budget and Policy Priorities 2021). To our knowledge, the only work examining the realized effects of the ARP in its totality on economic outcomes is Clemens et al. (2022), who aggregate the $6 trillion in pandemic-era allocations, including the ARP, and document minimal effects on income, output, and government employment.

A separate literature examines the effects of many of the programs within the ARP. A large literature exists on the short-run effects of the advanced and enhanced Child Tax Credit (CTC), generally finding that changes to the CTC under the ARP decreased child poverty and improved outcomes for families with children (Ananat et al. 2022; CLASP 2021; Han et al. 2022; Pilkauskas et al. 2022).[7] Other analyses focus on the distribution of ERA funds, particularly relative to the population that needed ERA (Figinski et al. 2024; Hepburn et al. 2022; OES 2022). Still other analyses focus on the degree to which pandemic-related stimulus, including the ARP, replaced lost earnings, finding that it was more progressive than that of the previous two U.S. recessions, primarily reflecting more generous stimulus payments and unemployment insurance (Larrimore et al. 2022, 2023; Ganong et al. 2022). Other evidence suggests that the increased fiscal support kept consumer spending high even in lower-income areas that experienced significant job losses (Chetty et al. 2022) and that the increased availability of federal stimulus, specifically the expansion of unemployment insurance, had a relatively small effect on employment (Ganong et al. 2022).[8]

[7] Lippold and Luczywek (2023) find that the CTC expansion lowered employment but the reduction in wages was offset by increases in self-employed income. Additional analyses of the costs of making the advanced and enhanced CTC included in the ARP permanent, such as Goldin et al. (2021), find that the benefits of making the changes permanent would exceed the costs.

[8] Coibion et al. (2020), studying the stimulus payments under the CARES Act, find that households used the stimulus to increase consumption (40 percent), pay down debt (31 percent), and augment savings (27 percent).

Our work also contributes to a literature that analyzes the geographic distribution of federal stimulus spending. Boone et al. (2014) study the 2009 stimulus law and find that it allocated more funds per capita to high-poverty congressional districts, but not to high-unemployment districts. Gimpel et al. (2012) similarly study ARRA, concluding that neither low-income counties nor counties that experienced the most severe job losses during the Great Recession received more stimulus funds. Faulkender et al. (2023) and Granja et al. (2022) evaluate the geographic distribution of federal funds provided by the Paycheck Protection Program (PPP) in the wake of the pandemic. The former show that county-level funding can depend on the outlets through which outlays are disbursed, e.g., community banks, while the latter find little evidence that the hardest-hit areas received more funds—in fact finding the reverse to be true. The distribution of federal stimulus funds has also been found to reflect the history of a region, for instance, past economic shocks to SNAP participation (Slack and Myers 2014), as well as non-economic considerations, such as the political lean of legislators.[9]

[9] For instance, counties tend to receive greater federal outlays when they are represented by legislators in the same political party as the president (Berry et al. 2010), though political targeting through discretionary spending may be muted within fiscal stimulus programs such as ARRA (Boone et al. 2014).

2. Data, Methods, and Summary Statistics

Data and Methods

We focus on 31 of the largest programs enacted under the ARP for which reporting data are available, excluding grant programs that totaled less than $1 billion or could not be readily mapped to counties.[10] Details for each program are available in Table 1. Collectively, these 31 programs account for approximately 61 percent ($1.15 trillion) of the total estimated ARP spending ($1.9 trillion). Some programs provided aid directly to individuals, such as EIPs, enhancements to the Child Tax Credit (CTC), and increased food assistance benefit amounts provided by the Supplementary Nutritional Assistance Program (SNAP). While individuals and households ultimately benefited from many other programs, such as ERA and the Homeowners Assistant Fund (HAF), the federal government provided the funding in the form of grants to state and local governments, who were ultimately responsible for identifying and screening eligible individuals and households. Some ARP programs provided direct assistance to businesses, such as the Economic Injury Disaster Loan (EIDL). Still other programs provided aid directly to state and local governments (through, for example, the State and Local Fiscal Recovery Funds) to support recovery from the pandemic.

[10] Given that these 31 programs together constitute $1.15 trillion in federal outlays, any program that we exclude for comprising less than $1 billion would represent less than 0.09 percent of the federal outlays tallied. Grants that could not be distributed across counties includes, for instance, ones that were allocated to transit systems, airports, and rural hospitals.

Table 1: Overview of Programs

Program	Abbreviation	Reported Geography	Assumption to Distribute from Reported Geography to Counties	Amount Accounted For ($b)
ARP Economic Impact Payment	EIP	County	Actual	349.3
State and Local Fiscal Recovery Funds				
State Grants	SFRF	State	Population	195.3
County Grants	COUNTY	County	N/A - Distributed to the county	64.4
Metro City Grants	METRO	City	Population	44.8
Tribal Grants	SLFRF TRIBES	Tribal Statistical Area	Population	20.0
Non-Metro City Grants	NEU	City	Population	19.2
Elementary and Secondary School Emergency Relief Fund	ESSER3	School District	Population ages 5-17	98.1
Child Tax Credit (ARP increase)	CTC	County	Actual	88.9
Childcare Funds	CHLDCR	State	Population under 5	37.3
Pandemic Electronic Benefit Transfer	PEBT	State	Population in poverty under 18	36.9
Higher Education Emergency Relief Fund	HEERF	College (Zip)	Assigned to the county of the institution	35.2
Restaurant Revitalization Fund	REST	Address	N/A	28.4
Emergency Rental Assistance	ERA	State or City	Renting Population	21.2
Shuttered Venue Operators Grant	SVOG	Address	N/A	14.5
School COVID Testing	TESTING	State	Population ages 5-17	9.9
Child and Dependent Care Tax Credit (ARP increase)	CDCTC	County	Actual	9.8
Earned Income Tax Credit (ARP increase)	EITC	County	Actual	9.6
Capital Projects Fund	CP	State	Population	9.6
Homeowner Assistance Fund	HAF	State	Households with a mortgage	9.3
State Small Business Credit Initiative	SSBCI	State	Population	8.0
Economic Injury Disaster Loan Advances	EIDL	State	Population	7.4
15% Increase in SNAP Benefits	SNAP	State	Households receiving SNAP or cash aid	6.7
Community Health Centers	CHCS	City	Population	6.0
Low Income Home Energy Assistance Program	LIHEAP	State	Population with income <= 150% of the poverty level	4.4
Mental Health & Substance Abuse Block Grants	SAMHSA	State	Population	2.9
Individuals with Disabilities Education Act Grants	DISEDUC	State	Population with disabilities under 18	2.9
Emergency Assistance to Non-Public Schools	PRIVSCHL	State	Population ages 5-17	2.6
Historically Black Colleges and Universities	HBCU	College (Zip)	Assigned to the county of the institution	1.6
Local Assistance and Tribal Consistency Fund	LATCF	County	Population	1.5
Older Americans Act Grants	ELDERS	State	Population 65 and over	1.4
Build Back Better Challenge Grants	BBBCHAL	County or similar	Population	1.0

Note: "Amount Accounted For" is the dollar amount in available reported data, not necessarily the amount allocated to the program in total. Spaces between programs are to assist with readability. We provide additional detail on the programs and our assumptions in Appendix A.

While two of the programs we study report spending by recipient address (grants for restaurants and shuttered venues), for all other programs we utilize allocations at an aggregated geography level, i.e., the state, city, county, or school district. These allocations are the amount the federal government provided to that aggregated geographic level.[11] We convert each of these geographies into their respective counties using crosswalks from the Missouri Census Data Center. The relevant population for distributing each program's funds is included in Table 1. (In Appendix A, we provide additional information on how the funds were allocated.)

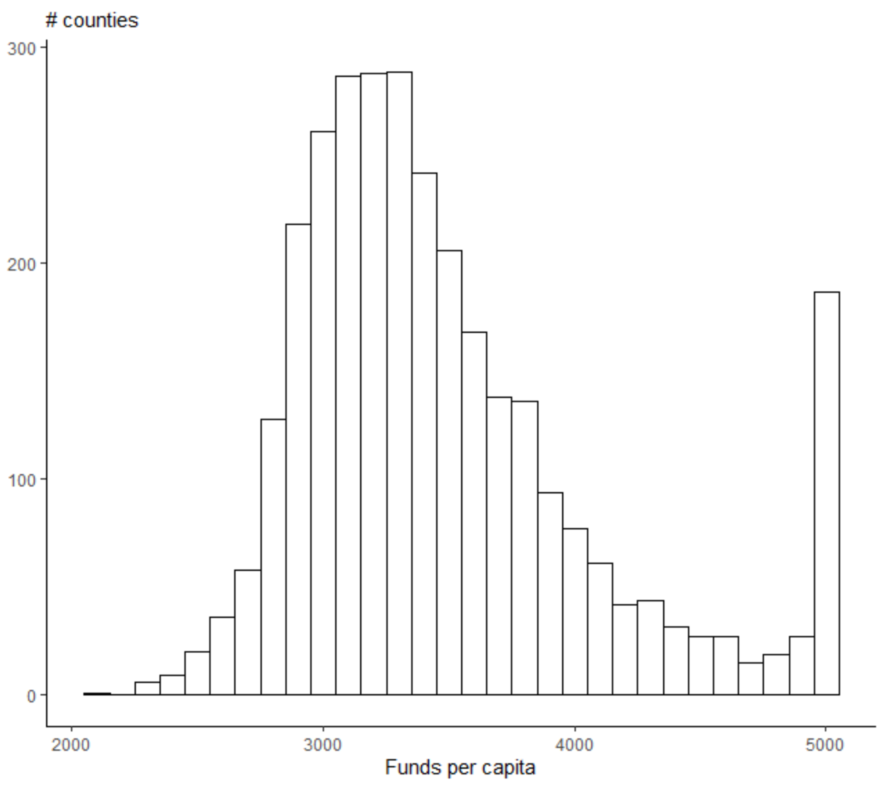
We note here that our study examines how the ARP funds *could have been distributed*, not how ARP funds were *actually distributed*. We cannot observe the actual distribution of funds within these reported geographies because these data do not exist for all ARP programs. Instead, we assume the funds were distributed in proportion to the relevant population within both the reported geography and the county that could potentially have been eligible for the program. In doing so, we attempt to identify the broadest eligible population in an effort to have our assumptions have the least effect on our findings. For example, HAF provided financial assistance to homeowners who had incomes below a certain level. However, the data available to us only include the number of homeowners in each county with a mortgage. As a result, it is likely that the HAF funds were more targeted than our assumption would assume. Because we use the broadest population potentially eligible for each program, it is likely that if we had more precise information on the geographic distribution of all funding from the various sources we study, the funding would be more targeted to economic need than our results suggest.

[11] The expenditures on EIPs, expanded CTC, expanded childless Earned Income Tax Credit (EITC), and enhanced Child and Dependent Care Tax Credit (CDCTC) are available with information about the individual's address. However, we did not have access to taxpayer data. Instead, the Office of Tax Analysis (OTA) generously prepared and provided us, in response to a request by the Office of Economic Policy for this project, with the amount of the EIPs, expanded CTC, expanded EITC, and CDCTC individuals in each county received. Staff of OTA accessed the confidential taxpayer data, which was kept in a secured Treasury or IRS repository, and all results were reviewed prior to their distribution to the Office of Economic Policy to ensure that no confidential information was disclosed.

Summary Statistics

The per-person distribution of ARP funds across the 3,143 counties is somewhat diffuse and exhibits an extreme right tail (Figure 2). Though the standard deviation is large and the mean is well above the median, 80 percent of people live in counties that received between \$2,900 and \$4,300 per person (Table A-1).[12] When we consider funds as a fraction of average annual income rather than per person, the distribution of which is presented in Figure A-1, we estimate that the ARP delivered on average an 11 percent boost in annual income, with 90 percent of counties receiving a transfer equivalent to at least 6 percent of average annual income.

Figure 2: Distribution of Funds per Capita Across Counties



Note: Values above \$5,000 per person are top-coded (182 counties containing 2 percent of the population). We provide a version with funds per capita as a share of county income as the x-axis in Figure A-1 and a version of this graph weighted by population in Figure A-2.

[12] Examining the distribution of counties, 80 percent received between \$2,900 and \$4,400 per person (Table A-1).

Narrowing in on the long right tail, we see that 182 counties (representing 2 percent of the U.S. population) received more than $5,000 in ARP funds per person. Residents in these counties received at least 49 percent more than residents in the median county (who each received about $3,300). Decomposing the distribution of per-capita ARP funds into each of the 31 programs reveals that these outlier counties are mostly beneficiaries of SLFRF tribal funds and grants to school districts. If we were to exclude tribal funds, 63 percent of these 182 counties would have received less than $5,000 per capita (not including programs not captured in our data) because tribal lands tend to be in counties with smaller populations (Table A-2). Further excluding school district funds would result in 90 percent of these counties falling below the $5,000 per-capita amount (Table A-2).

To better understand the variation in how ARP funds were dispersed across counties, we consider several demographic variables. These demographic measures pertain to poverty, education, employment, race, and health insurance coverage, and are produced using data from the 5-year 2015-2019 American Community Survey (accessed from IPUMS NHGIS) (Manson et al. 2022). Summary statistics for each characteristic across the 3,143 counties are available in Table A-1.

Data Limitations

Our analysis is necessarily limited by the data we can access. While our 31 programs account for $1.15 trillion in spending, this constitutes only 61 percent of total estimated spending provided by the ARP. The largest funding source we are unable to analyze is the estimated $206 billion in the expansion of unemployment insurance (UI).[13] We anticipate, however, that the distribution of such funds through additional UI would be similarly related to economic need as

[13] For cost estimates see CBO's "Estimated Budgetary Effects of H.R. 1319, American Rescue Plan Act of 2021," Detailed Tables, Title 9, March 10, 2021 (accessed 01/25/2023; https://www.cbo.gov/publication/57056).

the programs we examine here. Existing analyses on the distribution of fiscal stimulus in response to the pandemic find that UI provided the largest supplement to households in the bottom of the income distribution (Larrimore et al. 2022, 2023). Thus, we do not believe that the omission of UI funds from our totals qualitatively affects our takeaways.

Our analysis is further limited by the assumptions required to allocate funds from reported geographies, such as states and cities, to counties. Some of these assumptions are arguably less plausible than others. For instance, it seems reasonable that counties with a greater number of SNAP recipients before the ARP continued having more SNAP recipients in 2021 after the ARP. However, it may be less reasonable to assume that state SLFRF funds were distributed evenly across all residents of a given state.[14] We recognize the limitations of our assumptions, but at the same time, make the decision to employ such assumptions, as they are necessary to achieve a county-level distribution. This is because more-granular reporting data have not been collected for many of these programs, and in some cases, could not have been.[15]

Finally, our analysis overlooks within-jurisdiction spending priorities by state and local officials, which could reverse our results. Perhaps ARP funds were allocated to higher-poverty states, but state actors chose to purpose such funds toward areas with less poverty or economic need. While this would certainly be relevant for understanding the combined efforts of federal, state, and local policymakers, our primary focus is on the federal role in distributing ARP funds.

[14] While it also may be less reasonable to assume that SLFRF funds were distributed evenly across all residents in a given county, we do not need to make such an assumption because we are examining the funds per capita at the county-level. Most cities are entirely contained within a county. However, when cities cross county borders, we distribute the city's SLFRF funds to the various counties based in proportion to the population of the city that resides within each county.

[15] Consider SLFRF funds, which could be used for state government "revenue replacement." It is difficult to measure what spending would have been reduced had these funds not been available.

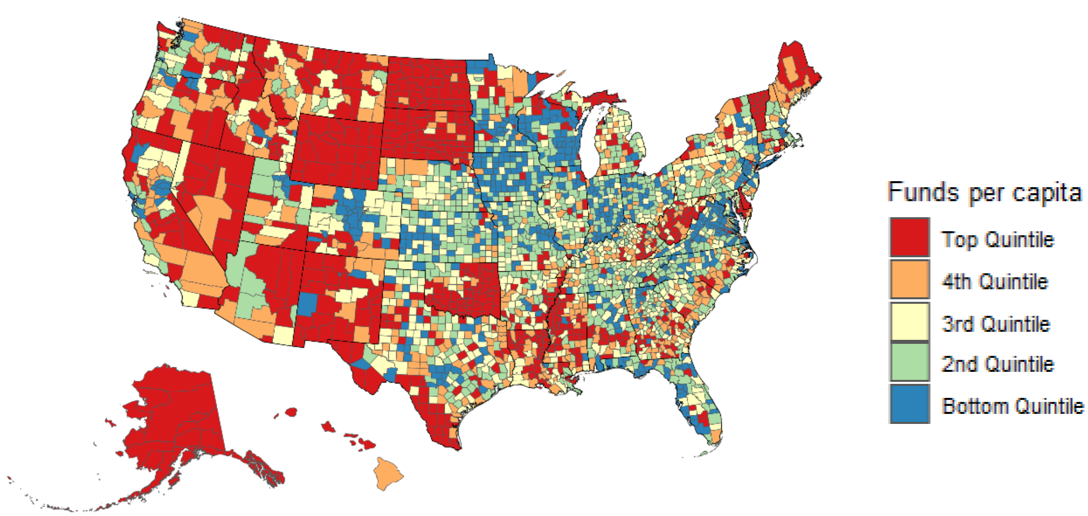
3. Where Did the Funds Go?

Our analysis reveals that several types of counties received more ARP funds than others, including counties in small-population states (detailed in Section 3.1), high-poverty counties (detailed in Section 3.2), majority-minority counties (detailed in Section 3.3), and counties that saw larger increases in the unemployment rate during the pandemic (detailed in Section 3.4). Much of this variation is not detectable at the state level, highlighting the importance of considering more granular geographies.

3.1 Geography

We begin our discussion of where ARP funds went with respect to geography. We plot in Figure 3 the distribution of per-capita ARP funds across U.S. counties. Counties that received more ARP funds per capita are shaded red while those that received less are shaded blue. We note two key takeaways.

Figure 3: Funds per Capita Across U.S. Counties



Note: Figure displays county-level per-capita allocations. We provide a version of this graph weighted by population in Figure A-3 and a version with funds per capita as a share of county income in Figure A-4.

First, several less-populated states received above-average allocations, including Alaska, Delaware, New Mexico, North Dakota, South Dakota, Vermont, West Virginia, and Wyoming. This pattern stems from some fraction of funds being distributed on a per-state basis rather than a per-person basis, leading to greater per-capita allocations in smaller states. For example, $25.5 billion of the $195.3 billion in State Fiscal Recovery Funds (SFRF) grants were distributed on a per-state basis. This $500 million grant to each state translated into $867 per resident for Wyoming, but only $13 per resident for California. If the SFRF had instead distributed the $25.5 billion in proportion to the unemployed population, as were the other approximately $169 billion of funding, then the approximate $2,000 disparity in per-capita funds between Wyoming and California would have been 47 percent narrower.[16] Other programs such as ERA, HAF, Capital Projects, and State Small Business Credit Initiative (SSBCI) also included minimum allocations, which similarly contributed to the large per-capita funding disparity we observe toward less populous states.[17] Second, as we noted for the justification of this paper, examining ARP allocations at a more granular level of geography offers insights beyond simply looking across states. County-level allocations in Texas, for instance, range from approximately $3,000 to $6,000 per person, and those in New York range from approximately $3,000 to $5,500 per person.

3.2 Economic Need

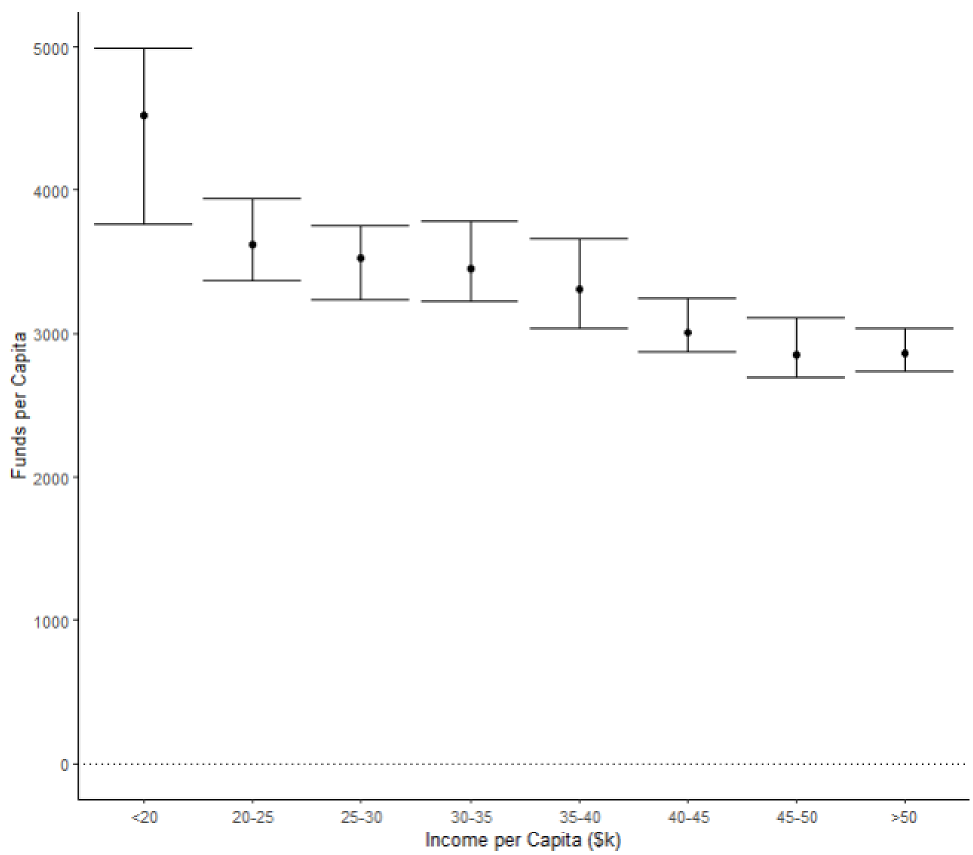
While understanding the distribution of ARP funds on a per capita basis is useful for accounting for the size advantage of more-densely populated areas, the per-capita basis may be a less relevant measure to understand the impact of the fiscal stimulus. From the perspective of

[16] SFRF delivered the remaining approximately $755 million to the District of Columbia, which is equal to the amount that the District of Columbia would have received from the Coronavirus Relief Fund (CRF) had the District of Columbia been treated as a state rather than as a territory under the CRF allocations provided by the CARES Act.
[17] The correlation between state-level per-capita ARP funds and state population is a statistically significant -0.32, using Pearson's product moment correlation coefficient.

offering economic stimulus, policymakers may be concerned not only with the amount of funds allocated to an area, but whether the stimulus dollars reached disadvantaged communities.

We first consider the relationship between ARP funds and economic need by summarizing the distribution of ARP funds per capita by income per capita across counties in Figure 4. For ease of exposition, we group counties by their average income into $5,000 bins, with wider ranges at either end. In the figure, the dots represent the median ARP funds per capita across the counties within each bin, while the vertical bars span the 25th and 75th percentiles.

Figure 4: Median and Interquartile Range (25th to 75th Percentile) of ARP Funds per Capita by County Income per Capita



Notes: Dots show the median and the vertical bars the 25th and 75th percentiles of ARP funds per capita within $5,000 bins. All statistics are population weighted. Each income bin contains at least 25 counties. Figure A-5 displays the same graph with the y-axis as funds per capita as a share of county income.

There is a clear downward-sloping relation between the amount of ARP funds a county received per capita and its average income per capita. Broadly speaking, the lowest-income counties received the greatest amounts in ARP funds per capita. Counties with average incomes below $20,000 received about $4,500 in ARP funds per capita at the median, with about $1,200 differentiating the 25th and 75th percentiles. On average, counties with average incomes below $20,000 received about $4,900 of ARP funds per capita. For such counties, this injection of funds, on average, was equivalent to about 25 percent of annual income per capita (see Figure A-5). Although higher-income counties received funds as well, these counties received a substantially smaller amount. Counties with average incomes per capita above $50,000 received a median of $2,900 in ARP funds per capita, nearly 40 percent less than counties in the lowest average income category.[18] For such counties, the amount of ARP funds allocated from these programs was equivalent to around 5 percent of annual income per capita (Figure A-5).

In addition to considering the direct relationship between ARP funds and income, we also consider the relationship between the distribution of ARP funds and other county-level observables, such as demographics and alternative measures of economic need. Specifically, we examine the correlation between the per capita amount of ARP funds a county received and the share of the county's population with income below the federal poverty line, receiving public assistance income, receiving Medicaid benefits, or without health insurance. We also examine the correlation between the per capita amount of ARP funds and each county's average rent burden as a share of income and employment-to-population ratio. Finally, because many economic indicators, such as the share of the population below the federal poverty line or the

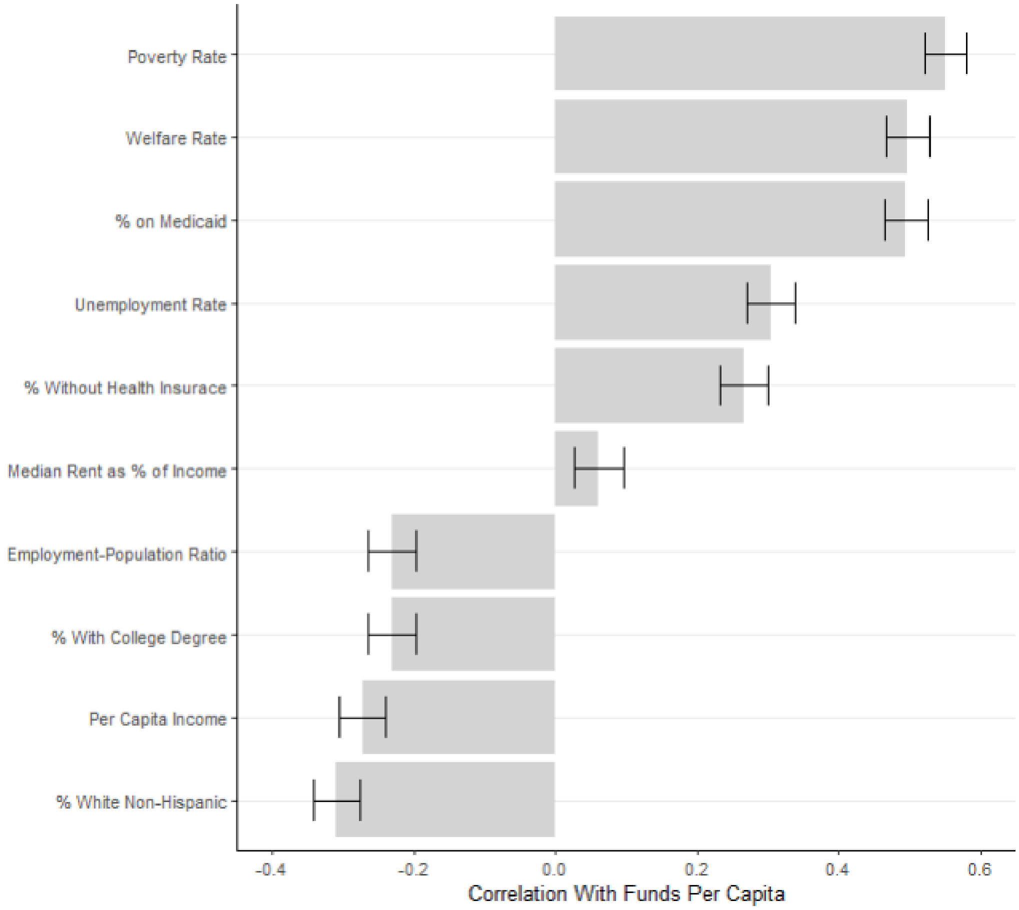
[18] The difference between mean ARP funds per capita in the lowest and highest income categories is statistically significant when regressing ARP funds per capita on indicators for the income categories and clustering standard errors at the state level.

employment-to-population ratio, are strongly related to race, ethnicity, and educational attainment, we examine the correlation between per-capita ARP funds and the percent of residents who are white and non-Hispanic or who are college graduates. For all these relationships, we use data from the American Community Survey (ACS) 2015-2019 five-year estimates to avoid any changes in the measures of economic need resulting from the pandemic.[19]

These correlations are displayed in Figure 5. We see that the ARP's grant programs delivered more aid to disadvantaged areas, with salient measures such as the poverty rate and the share of the population uninsured or receiving welfare being strong predictors of which counties received more in per-capita ARP funds. Other indicators reveal a similar pattern: areas with fewer resources were allocated more funds per capita. The poverty rate is the most notable among these as it is highly correlated with eligibility for public assistance and Medicaid. We also observe a robust correlation of 0.3 between per-capita ARP funds and the unemployment rate in October 2020, indicating that areas with more labor market slack received greater fiscal support.

[19] Our results are unchanged if we use the 2016-2020 five-year ACS estimates.

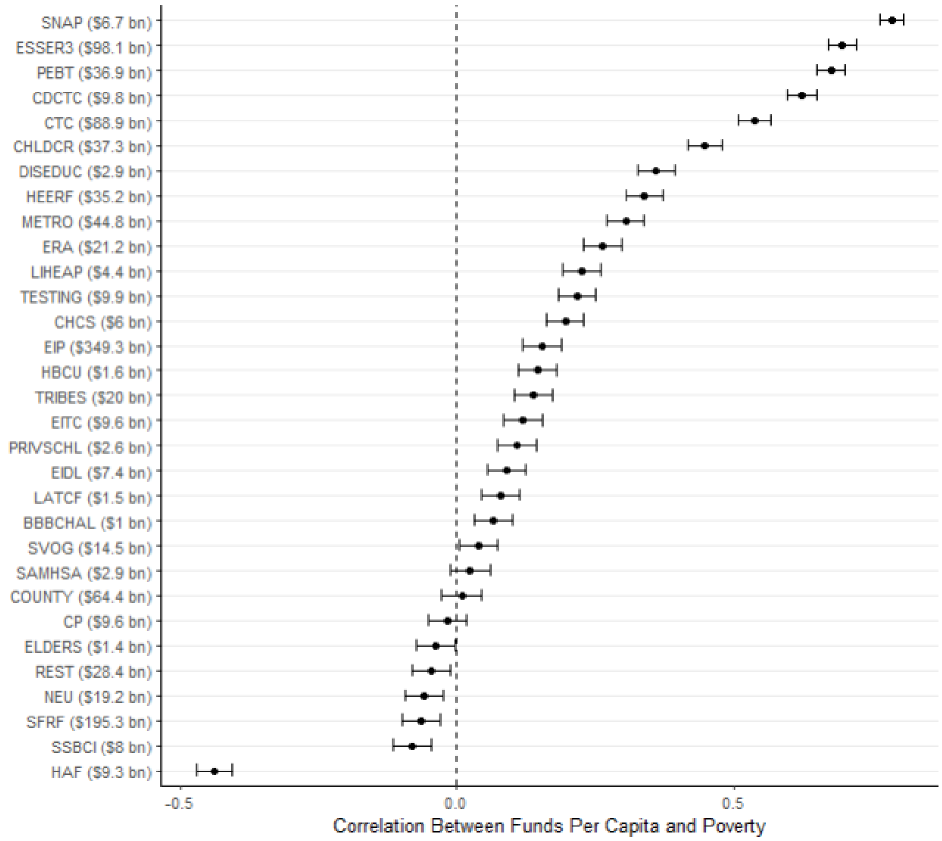
Figure 5: Correlation of County Demographics and Funds Per Capita



Note: All correlations are measured at the county level. Covariates are listed in descending order according to their correlation with ARP funds per capita. Data on all the variables other than the unemployment rate are from the 2015-2019 five-year ACS data. The unemployment rate data are for October 2020 and are from the Bureau of Labor Statistics Local Area Unemployment Statistics. Bars represent 95 percent confidence intervals. All specifications are population weighted. We provide a version of this graph using the funds per capita as a percent of income in Figure A-6.

Given that the pre-pandemic poverty rate is a salient measure of economic need and a strong predictor of ARP funds per capita, we next ask which of the 31 ARP programs we study fuels the relationship between ARP funds and poverty. To that end, we plot the pairwise correlation across counties between each program's per capita allocation and the county's poverty rate in Figure 6. The overall relation with poverty is largely driven by grants to school districts (ESSER3), SNAP benefit increases, Pandemic EBT (PEBT) for feeding low-income children, and expansion of the CTC. This is perhaps not surprising, given that ESSER3's allocation formulas explicitly targeted poverty, while SNAP and PEBT were available to households with incomes below or only slightly above the poverty threshold. Moreover, the expansion to CTC, which increased the dollar amount of the credit and made the full amount available to taxpayers with little or no income (i.e., fully refundable), increased the credit amount most for those at the bottom of the income distribution (who could not fully benefit from the non-ARP CTC because it is non-refundable).

Figure 6: Correlation Between Poverty and Funds per Capita by ARP Program



Note: Correlations are measured at the county level. Programs are listed in descending order according to their correlation with the poverty rate. Bars represent 95 percent confidence intervals. The correlations are population weighted by total county population. We provide a version of this graph using the funds per capita as a percent of income in Figure A-7. Data on the poverty rate are from the 2015-2019 American Community Survey 5-year estimates.

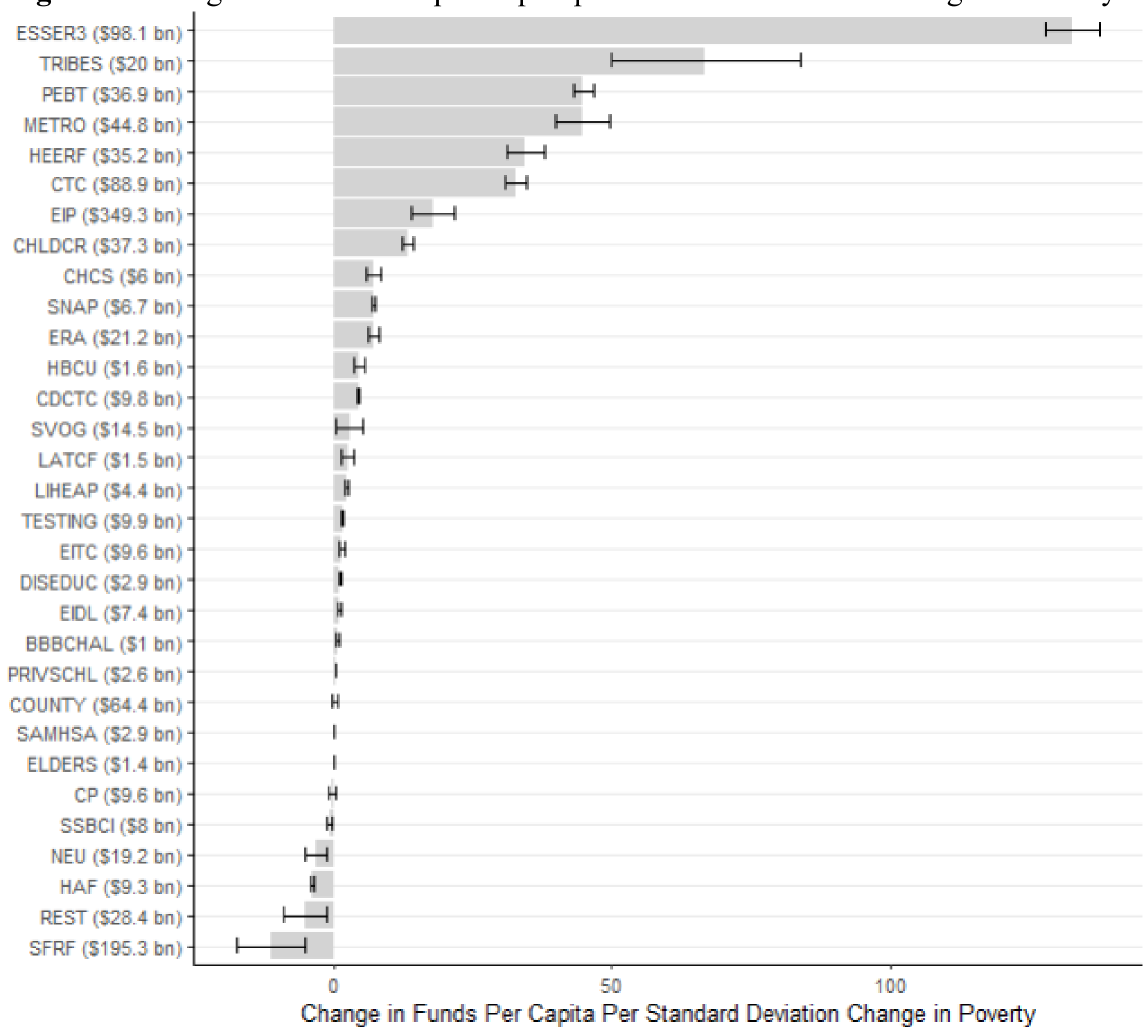
On the other hand, the SFRF allocations show a slightly negative correlation with poverty. This is in part due to the $25.5 billion in SFRF grants that were distributed by state instead of by population. The ten states with the smallest populations have a population-weighted average poverty rate of 12.2 percent, whereas the ten states with the largest populations have an average poverty rate of 13.9 percent. One clear outlier from the program-specific decomposition is that funds distributed through HAF exhibit a starkly negative relation with poverty, consistent with the program's inherent nature of targeting homeowners, who are 16 percentage points less likely than renters to have incomes below the poverty threshold.[20]

Although these correlations make it clear which programs most directly targeted U.S. counties with the greatest absolute levels of economic need as measured by poverty, they do not capture the relative size of each program or the amount of variation in each program's allocations. To determine which of these programs drove the overall relation between per-capita funds and poverty, we take the additional step in Figure 7 of scaling each program by its per-dollar relation with one standard deviation greater county-level poverty and weighting by overall county population. Two important findings emerge. First, the overall relation with poverty we document in Figure 5 is largely driven by two programs, Elementary and Secondary School Emergency Relief (ESSER3) and the amounts distributed to tribal governments (TRIBES). While a one standard deviation greater poverty rate (equivalent to 6 percentage points) is associated with an additional $400 per person in ARP funds, these two programs (ESSER3 and TRIBES) together account for one-half of that amount. Second, a number of programs, such as SNAP, pandemic EBT (PEBT), and childcare funds (CHILDCR), robustly target higher-poverty areas but, given the comparatively small funds allocated to these programs, contributed little to

[20] See https://data.census.gov/table?q=poverty+by+tenure+&tid=ACSDT1Y2021.C17019. Of the 60.7 million owner-occupied housing units, 3.0 million (or 4.9 percent) have incomes below the poverty line. Of the 21.8 million renter-occupied housing units, 4.5 million (or 20.8 percent) have incomes below the poverty line.

the overall relation with poverty. The same is true though of the programs that targeted counties with greater poverty the least, e.g., HAF.

Figure 7: Change in ARP Funds per Capita per Standard Deviation Change in Poverty



Note: Correlations are measured at the county level. Programs are listed in descending order according to their correlation with the poverty rate. Bars represent 95 percent confidence intervals. We are not changing the poverty rate, just moving one standard deviation of poverty and examining the change in dollars per capita delivered by each program to the county. The correlations are population weighted by total county population. Data on the poverty rate from the 2015-2019 American Community Survey 5-year estimates.

3.3 Race

In addition to economic need, we observe in Figure 5 that a county's racial composition is a strong predictor of its per-capita allocation of ARP funds. Is this a distinct effect or simply an artifact of the race-poverty correlation? To answer this question, in Figure 8, we explore a second dimension of variation beyond poverty: whether a majority of residents within the county are non-white or Hispanic. Evidently, even when holding poverty rates fixed, we find that majority-minority counties received greater per-capita allocations, on average.[21] Majority-minority counties received, on average, about $240 more in per-capita ARP funds than other counties with similar poverty rates.[22] This relation is largely attributable to the grants provided to large cities (i.e., metro cities funding) under SLFRF, which accounts for 43 percent of the difference, followed by restaurant grants (REST) (35 percent), SFRF (30 percent), and PEBT (20 percent).[23]

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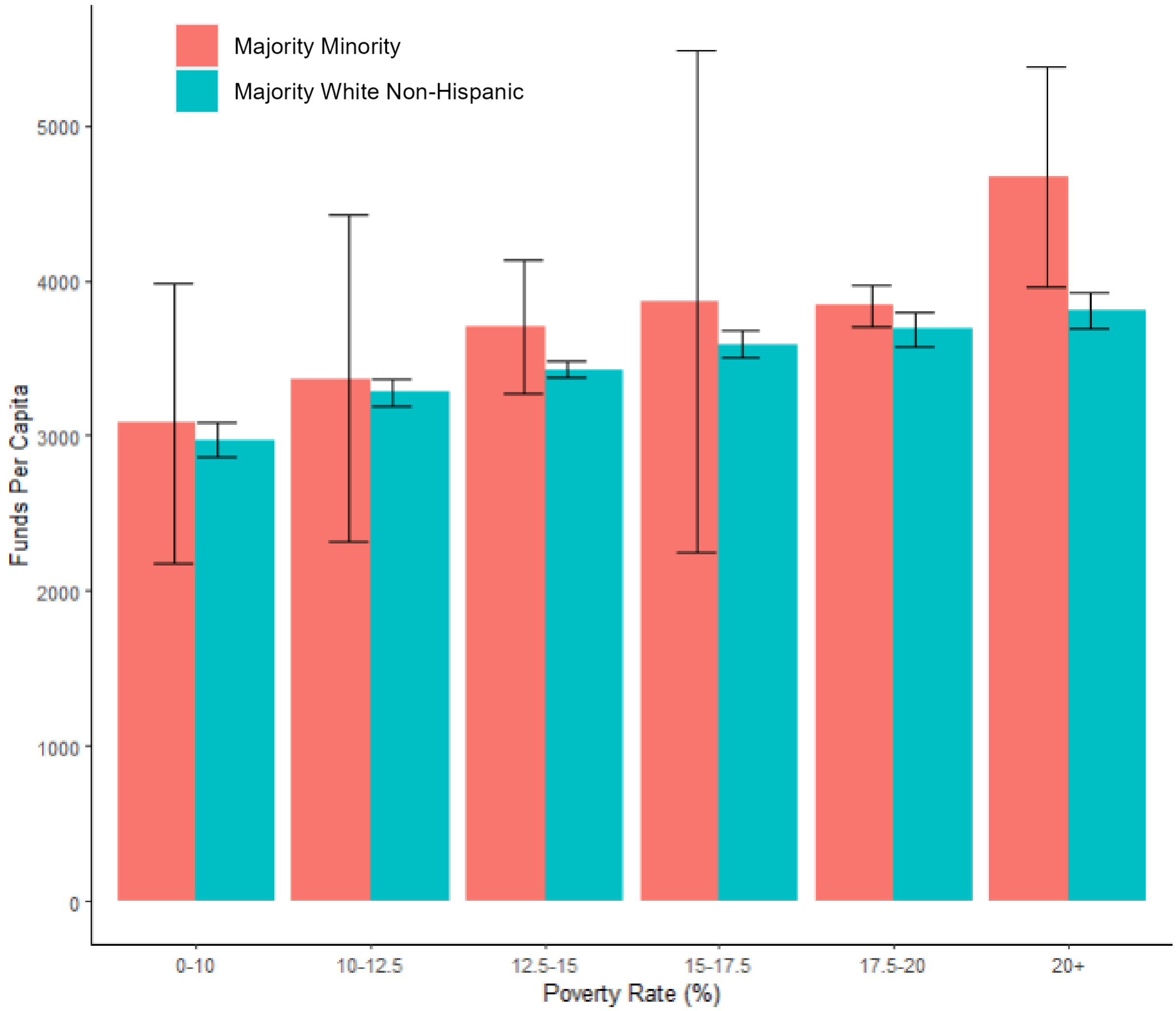
[21] Figure 8 somewhat understands the relationship given the number of poverty bins we create and the finite number of counties. When we regress ARP funds per capita on poverty rate and an indicator for whether the county is majority-minority, we find a strong and statistically significant relationship between ARP funds per capita and whether a county is majority-minority.

[22] To compute this average, we regress ARP funds per capita on the poverty rate and an indicator for whether the county is majority-minority, and report the coefficient on majority-minority, which is statistically significant at the 95 percent level.

[23] These add up to 128 percent because other programs contribute negatively to this effect.

Figure 8: Funds per Capita by Poverty and Majority-Minority Status



Note: Measured across counties. Bars represent a 95 percent confidence interval. Funds per capita are weighted by population. Table A-3 shows a tabular version of Figure 8. Figure A-8 provides the share of the population that is white non-Hispanic and non-white or Hispanic across the poverty bins. Data on the poverty rate, the share white non-Hispanic, and the share non-white or Hispanic are from the 2015-2019 American Community Survey 5-year estimates.

There are two elements of the metro cities funding that may have led to additional aid being allocated toward majority-minority counties. On the extensive margin, high-poverty majority-nonwhite counties are more likely to contain metro cities and thus be eligible for these funds, while high-poverty majority-white counties are less likely to contain a metro city. For example, 90 percent of residents in majority-nonwhite counties with poverty rates above 15 percent live in counties that contain a metro city. On the other hand, just 58 percent of people in majority-white counties with poverty rates above 15 percent live in counties that contain a metro city. On the intensive margin, each city's allocation was determined according to the Community Development Block Grant (CDBG) formula. In addition to the poverty rate, the CDBG formula considers other measures of disadvantage, such as overcrowded and pre-war housing and decelerating population growth.[24] These additional measures, which we do not observe, may correlate with race even after accounting for differences in poverty.

Next, we explore the impact of the State Fiscal Recovery Funds (SFRF) grants formula, which scaled with the unemployed population in each state in the fourth quarter of 2020, on the contribution to the majority-minority counties receiving more funds per capita conditional on poverty. States with a greater share of minority residents had higher unemployment rates during the fourth quarter of 2020, a relation we observe even after controlling for state poverty rates, which may explain SFRF's contribution to this pattern.[25] This effect is particularly notable because it outweighs a competing aspect of SFRF's design that directs funds toward states with predominantly white populations. The SFRF's small state minimum allocated $500 million to each state in addition to an allocation that scaled with unemployment. This further elevated the per-capita allocations in small states, which tend to have mostly white populations: The ten smallest states on a population basis are 77 percent white non-Hispanic, whereas the ten largest states are 54 percent white non-Hispanic. If these per-state funds were instead distributed in proportion to each state's unemployed population, as the remainder of SFRF was, then we estimate majority-minority counties would have received an additional $60 per capita on average.

[24] https://crsreports.congress.gov/product/pdf/R/R46733/2.

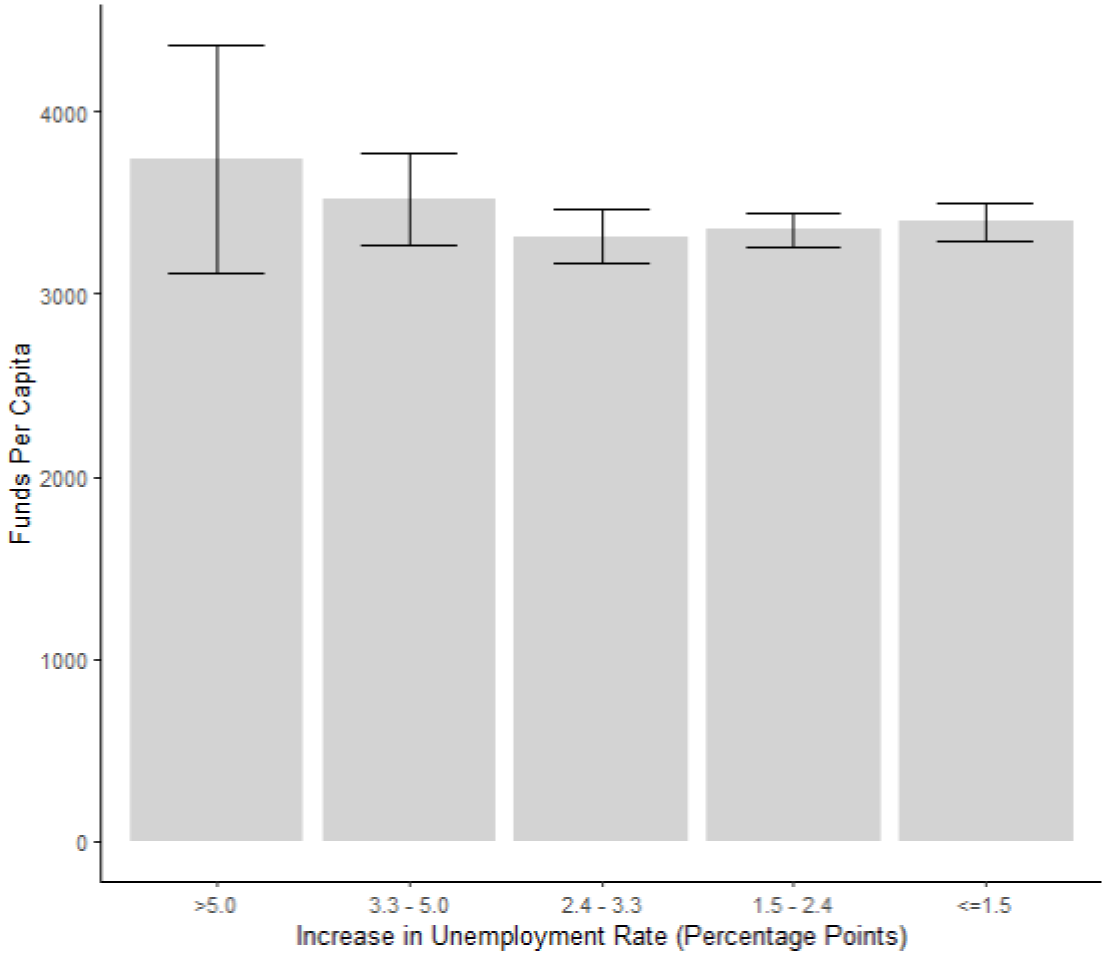
[25] For example, moving from the 10th percentile to the 90th percentile of state minority share (21 percent to 63 percent) is associated with a 2.8 percentage point increase in the state unemployment rate. This effect is identical when controlling for state poverty rate. A complete regression table is reported as Table A-4.

3.4 Pandemic Labor Market Distress

Finally, we examine whether the allocation of funds from these programs relates to labor market deterioration brought about by the pandemic recession. Policymakers may target fiscal stimulus toward areas with high levels of labor market distress because such areas were more exposed to the recessionary shock and additional stimulus may offer long-term benefits, such as enabling unemployed workers to find better-quality jobs (Nekoei and Weber 2017) and reducing foreclosures (Hsu et al. 2018). For our measure of labor market distress brought about by the COVID-19 pandemic, we take the change in county-level unemployment rates between October 2019 and October 2020.[26] To examine the relationship between increases in the unemployment rate and ARP funds per capita, we first plot, in Figure 9, the average funds per capita in each quintile of increases in the unemployment rate. Even though the average funds per capita are not statistically different across quintiles, we find suggestive evidence that counties that experienced more pandemic era labor market distress received more in ARP funds per capita.

[26] We repeat our analysis using the change in county-level unemployment rates between (1) October 2019 to December 2020 and (2) October 2019 to February 2021 and find similar results. See Tables A-5 and A-6. We additionally repeat the analysis for February 2020 to April 2020 and find smaller and less significant effects, possibly due to the short time horizon. See Table A-7. Finally, we examine the change in county-level employment levels, rather than changes in the unemployment rate, between October 2019 and October 2020 and find similar results to those using the change in the unemployment rate between October 2019 and October 2020. See Table A-8.

Figure 9: ARP Funds Per Capita by Quintile of Change in Pandemic Unemployment Rate



Note: The definition of quintiles and the amount of funds per capita are weighted by county population. Bars represent 95 percent confidence intervals. Data on the unemployment rate are from the Bureau of Labor Statistics (BLS) Local Area Unemployment Statistics (LAUS).

We more formally document the relationship across counties between the increase in the county unemployment rate and per capita ARP funds through a regression analysis in Table 2, which considers individuals equally by using population-based weights. We cluster the standard errors by state.

Table 2: ARP Funds per Capita by County and Increase in the Unemployment Rate, Poverty and Race

Dependent Variable:	Percent Change in Funds per Capita			
Model:	(1)	(2)	(3)	(4)
Increase in Unemployment Rate	1.759***	1.064*	0.344	0.880
	(0.393)	(0.555)	(0.592)	(0.870)
Poverty Rate		2.095***	1.977***	2.244***
		(0.139)	(0.141)	(0.124)
Share White Non-Hispanic			-0.114***	
			(0.032)	
State Fixed Effects	No	No	No	Yes
Observations	3,140	3,140	3,140	3,140
R^2	0.05	0.45	0.47	0.68

Note: The dependent variable in each specification is 100 times the logarithm of funds per capita. Each observation is a county. All specifications are population weighted. Standard errors are clustered by state. Data on the unemployment rate are from the Bureau of Labor Statistics (BLS) Local Area Unemployment Statistics (LAUS). Data on the poverty rate and the share white non-Hispanic are from the 2015-2019 American Community Survey 5-year estimates. One, two, and three stars reflect statistical significance at the 10, 5, and 1 percent levels, respectively.

Column 1 reveals a robustly positive relation between changes in the unemployment rate and the amount of ARP funds per capita distributed through these 31 programs to each county. A one percentage point increase in the local unemployment rate during the initial months of the pandemic is associated with 1.8 percent greater funds per capita received. In dollar terms, this translates into an additional $60 per person on average. This effect is in part attributable to the relation we observe between ARP funds and poverty. As such, the relation between per capita funds and increases in the unemployment rate attenuates in column 2 once poverty rates are included but remains significant at the 10 percent level at 1.1 percent (or $30 per person) per additional percentage point of unemployment increase during the pandemic's onset.

Next, given that Section 3.3 illustrates a relation between ARP funds and race that is distinct from economic need, we incorporate county-level demographics in Columns 3. Again, the relation between per-capita ARP funds and changes as the unemployment rate attenuates further. A one percentage point increase in the unemployment rate is associated with 0.3 percent (or about $10) more in per-capita funds, however, the relationship is no longer statistically significant – potentially because non-white individuals experienced larger increases in unemployment than white individuals (Fairlie, Couch, and Xu 2020, 2021).

When we incorporate state fixed effects—as to absorb all variation between states and isolate county-level variation within states—the relation between per-capita funds and changes in the unemployment rate remains positive at 0.9 percent more in per-capita funds per one percentage point increase in the unemployment rate. However, the relationship is not statistically significant.[27] In sum, even without accounting for the expansion of UI, which would have directly targeted labor market distress (e.g., increases in the unemployment rate), counties that experienced greater labor market distress received more in per-capita funds from the aggregation of these 31 ARP programs.

With regards to poverty, column 2 affirms the aforementioned positive association in Section 3.3: counties with a one-percentage-point greater poverty rate received on average nearly 2.1 percent more ARP funds per capita. Remarkably, incorporating the poverty rate into the regression model can explain an additional 40 percent of the county-level variation in (log) ARP funds per capita (as captured by the increase in the R^2). Column 3 demonstrates that areas with a greater minority population share received a greater per-allocation amount even conditional on poverty and labor market distress, although the relationship is not statistically significant. Since

[27] It seems plausible that if our data included the amount of funds distributed to each county through the expansion of UI, the coefficient on the unemployment rate may have remained statistically significant. However, we note UI would have needed to substantially increase the precision of the estimate as the current t-statistic is approximately one.

the poverty rate is positively correlated with the share of residents who are white and non-Hispanic, the relation between ARP funds per capita and the poverty rate weakens.

Our final model includes state fixed effects, so the coefficients only reflect within-state variation in funding, job losses, and poverty. This model explains 68 percent of the dispersion in (log) ARP funds per capita across counties. The coefficient on the poverty rate decreases slightly, indicating that differences across states cannot explain why counties with higher rates of poverty received more in ARP funds. Even when looking within the same state, counties with one-percentage-point greater increases in the unemployment rate or poverty received on average 0.9 and 2.2 percent more funds per capita, respectively. Thus, state-level trends or targeting cannot rationalize these county-level relationships.

Finally, we explore which of the 31 ARP programs we study drive these relations by correlating the county-level per-capita allocation for each individual program and county-level changes in the unemployment rate or poverty rate. We then produce a scatterplot in Figure 10 to relay the 31 pairs of these two unconditional correlation coefficients. On the x-axis, we report the correlation between county funds per capita and county change in the unemployment rate; on the y-axis, we report the correlation between county funds per capita with the county poverty rate. In turn, programs that lie in the top-right quadrant of Figure 9 positively correlate with both poverty and increases in the unemployment rate, whereas those in the bottom-left quadrant negatively correlate with both. Several notable patterns emerge.

Figure 10: ARP Program Correlations with Poverty and Pandemic Increases in the Unemployment Rate

Note: Correlation calculated across counties. Increases in the unemployment rate are measured by country between October 2019 and October 2020. All specifications are population weighted. Data on the poverty rate are from the 2015-2019 American Community Survey 5-year estimates. Data on the unemployment rate are from the Bureau of Labor Statistics (BLS) Local Area Unemployment Statistics (LAUS). Figure A-9 provides the program specific correlation between funds per capita and the poverty rate and the increase in the unemployment rate from October 2019 to December 2020. Figure A-10 provides the program specific correlation between funds per capita and the poverty rate and the increase in the unemployment rate from October 2019 to February 2021. Figure A-11 provides the program specific correlation between funds per capita and the poverty rate and the increase in the unemployment rate from February 2020 to April 2020.

First, funds distributed under SNAP and PEBT exhibit a strong positive correlation with increases in the unemployment rate in addition to poverty. This may in part reflect how eligibility for these programs is determined in real time based on household income, but also how pandemic-induced job losses were largely concentrated in lower-paying industries, such as leisure and hospitality and health services, and even more so in relatively lower-paying, fewer-hours occupations within such industries.[28] While metro cities funds were not targeted in the same real-time manner, urban areas saw outsize job loss due to the pandemic and as a result, we observe a strong correlation with the change in the unemployment rate and the SLFRF metropolitan cities (METRO) funding as well.[29]

Second, some programs exhibit a strong correlation with one of these two measures but not the other. Aid to elementary and secondary schools (ESSER3) shows a sizable correlation with poverty but little correlation with increases in the unemployment rate, perhaps since ESSER3 funds were allocated based on poverty and not increases in the unemployment rate. Grants to distressed businesses (EIDL) and restaurants (REST) display significant correlations with increases in the unemployment rate but not with poverty. While increases in the unemployment rate and business distress are, perhaps unsurprisingly, closely linked, the relationship between business distress and poverty is less so.

Third, there are some programs that display a negative or no relationship with both measures. HAF, in particular, stands out as an outlier in this regard, as its allocation inversely relates to both poverty and pandemic-induced labor market slack—perhaps since the program targets homeowners. However, we only observe state-level variation in these programs' allocations. Although states with lower levels of need received larger allocations, these states may have distributed such funds to high-need individuals amongst their populations. Grants to states to fund services for older Americans show a negative correlation with poverty in our data, since individuals ages 65 and older are, due to Social Security, somewhat less likely to have

[28] https://www.epi.org/publication/swa-2020-employment-report/.
[29] https://www.brookings.edu/blog/the-avenue/2020/04/29/which-city-economies-did-covid-19-damage-first/.

incomes below the poverty line.[30] That said, the services provided by grants to fund services for older Americans were likely targeted toward the significant number of elders in poverty.

[30] https://www.census.gov/content/dam/Census/library/publications/2022/demo/p60-277.pdf. The overall poverty rate in 2021 was 11.6 percent, whereas the poverty rate for individuals older than age 65 was 10.3 percent.

4. Concluding Remarks

The fiscal response to the COVID-19 pandemic was the largest federal injection of funds into the U.S. economy since the Second World War. The tail end of that response included the American Rescue Plan, a $1.9 trillion spending package. This work traces the distribution of 61 percent ($1.15 trillion) of those ARP funds across U.S. counties and reveals five key takeaways. First, we observe substantial dispersion in counties' per-capita allocations both across and within states, with several less-populated states receiving more funds per capita due to the ARP's small-state minimums. Second, counties with greater economic need received more in funds: a one-percentage-point greater poverty rate is associated with two percent greater per-capita dollars. Third, majority-minority counties on average received more funds per capita even after accounting for each county's poverty rate, largely reflecting how funds were distributed through the metro cities program. Fourth, counties that experienced greater increases in the unemployment rate in the wake of the pandemic recession received more funds per capita, in part because such counties displayed greater economic need before the recession. Finally, certain programs included in the ARP targeted job loss and poverty better than others. Disaggregating county-level funds, we find that food assistance, SNAP and PEBT targeted to counties with both economic need and increase in the unemployment rate.

Our analysis is limited by at least three factors. First, because we lack information on precise geographic spending of nearly all ARP dollars, we have to make assumptions about how the funding delivered to various governments, people, and entities was spent. These distributional assumptions are admittedly more reasonable for some ARP programs than others. For example, while HAF benefited homeowners who tend to be less likely to experience poverty and we assume that HAF dollars are distributed across counties within a state based on each county's share of homeowners with a mortgage within the state, HAF dollars almost certainly went to a smaller subset of homeowners with economic need. Nevertheless, we view our results as a lower bound, allowing future policymakers to assess whether various types of stimuli are likely to reach needy communities.

Second, our analysis is limited by the amount of ARP funds we are able to analyze. We are unable to examine the geographic distribution of approximately 40 percent, or about $0.75 trillion, of ARP's total spending. While many of the programs we exclude are smaller programs providing less than $1 billion each or programs that delivered aid to entities for which it is difficult to allocate the funds geographically (e.g., transit systems), the unemployment insurance (UI) enhancement is notably excluded from our analysis. The UI enhancement accounted for slightly more than 10 percent of all ARP funding and accounts for 25 percent of ARP funds missing from our analysis. However, while the UI enhancement is notably excluded, we anticipate, given the existing evidence examining the pandemic era expansion of UI showing that the lower income households received more UI, that including UI enhancement would only serve to elevate our key findings that ARP funds reached counties with higher poverty rates and larger pandemic increases in the unemployment rate.

Finally, our analysis does not speak to the efficacy of the ARP program, the efficiency of the timing of ARP spending, the multiplier effects such spending had on local economic activity, or the effects related to implementation decisions made by federal, state, and local governments. While we address how well-targeted the ARP funds were, this work cannot speak to whether the ARP led to improved socioeconomic outcomes, nor does it address optimal timing of spending by each ARP program. Because the ARP allowed many programs to spend funds over several years, it is possible that some ARP spending lagged behind others. Given the duration and economic consequences of the pandemic, it may have been more desirable to spend certain funds immediately to address need and spend other funds later to address knock-on effects from the pandemic. Answering such questions we believe would further aid future policymakers in designing fiscal stimulus.

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Appendix A: ARP Allocation Details and Distribution Assumptions

ARP Economic Impact Payments (EIPs) = $349.3 billion

Allocation formula: EIPs were distributed to individuals if they had incomes below certain thresholds. In general, taxpayers received $1,400 per individual on the tax return contingent on household income less than $80,000 for a single taxpayer and $160,000 for married taxpayers filing jointly. For more detail, see https://www.irs.gov/newsroom/more-details-about-the-third-round-of-economic-impact-payments.

Data on allocations: The Office of Tax Analysis (OTA), in response to a request by the Office of Economic Policy, prepared and provided the total amount of EIPs received by taxpayers within each county.

Assumption to distribute funds to each county: None. We use the actual observed spending amount as provided by OTA.

State and Local Fiscal Recovery Funds: State Grants = $195.3 billion

Allocation formula: Grants to states under the State and Local Fiscal Recovery Funds (SLFRF) were allocated using three formulas:

1. $169 billion distributed to states based on each state's share of the average number of unemployed individuals from the fourth quarter of 2020 (October 2020 to December 2020) as measured by the Bureau of Labor Statistics Local Area Unemployment Statistics.

2. $25.5 billion distributed to states equally such that each state received $500 million.

3. $755 million distributed to the District of Columbia, which is equal to the difference between the amount that the District of Columbia would have received from the Coronavirus Relief Fund (CRF) had the District of Columbia been treated as a state rather than as a territory under the CRF allocations provided by the CARES Act.

Additionally, the state grants under SLFRF included a minimum, which required that no state could receive less from SLFRF state grants, SLFRF county grants, SLFRF metro city grants, and SLFRF non-metro city grants combined than it did under CRF.

Data on allocations: Allocations are available at: https://home.treasury.gov/system/files/136/fiscalrecoveryfunds-statefunding1-508A.pdf.

Assumption to distribute funds to each county: SLFRF state grants are distributed to each county based on the county's pro-rata share of the total state population.

State and Local Fiscal Recovery Funds: County Grants = $64.4 billion

Allocation formula: Grants to counties under the SLFRF were allocated based on each county's pro-rata share of the total population within all counties. There was a minimum that required that no county that was classified as an urban county in FY 2021 could not receive less funding than if the SLFRF county grants were allocated to urban counties and metropolitan cities based on the Community Development Block Grant formula.

Data on allocations: Allocations are available at: https://home.treasury.gov/system/files/136/fiscalrecoveryfunds_countyfunding_2021.05.10-1a-508A.pdf.

Assumption to distribute funds to each county: None, funds are distributed to the county-level.

State and Local Fiscal Recovery Funds: Metro City Grants = $44.8 billion

Allocation formula: Grants to metropolitan cities under the SLFRF were allocated based on the Community Development Block Grant (CBDG) formula. The CDBG formula uses several factors to distribute the funds to cities: poverty, population, housing overcrowding, pre-1940 housing, and the population growth lag. Generally, cities are classified as metropolitan cities if (1) the city has a population of at least 50,000 people and is within a metropolitan statistical area or (2) the city is a principal city of a metropolitan statistical area.

Data on allocations: Allocations are available at: https://home.treasury.gov/system/files/136/fiscalrecoveryfunds-metrocitiesfunding1.pdf.

Assumption to distribute funds to each county: Funds are distributed pro-rata to each county based on the share of the population of each metropolitan city within each county.

State and Local Fiscal Recovery Funds: Tribal Grants = $20.0 billion

Allocation formula: Grants to tribal governments under the SLFRF were allocated using three formulas:

1. $1 billion was evenly distributed across all eligible tribes.

2. $12.35 billion were allocated to tribes based on each tribe's pro-rata share of total tribal enrollment among eligible tribes.

3. $6.65 billion were allocated to tribes based on each tribe's share of total tribal employment. The tribal employment allocation included a minimum such that no tribe could receive less than $1 million.

Data on allocations: Utilize tribal allocations from Henson et al. (2021).

Assumption to distribute funds to each county: For tribes that can be matched to a Tribal Statistical Area (TSA), the tribal grant funds are distributed to each county based on the pro-rata share of the TSA residing within each county. For tribes that cannot be matched to a TSA, the tribal grants are either assigned to the county where the tribe has lands or to the county where the tribe is headquartered.

State and Local Fiscal Recovery Funds: Non-Metro Cities Grants = $19.2 billion

Allocation formula: Grants to non-metropolitan cities (i.e., non-entitlement units of local government) are first distributed to each state based on each state's pro-rata share of the total population not residing within a metropolitan city. States were then required to distribute the funding to each eligible non-metropolitan city based on the non-metropolitan city's share of the state's total population residing within non-metropolitan cities. Allocations to non-metropolitan cities could not exceed 75 percent of the non-metropolitan city's most recent budget as of January 27, 2020.

Data on allocations: Internal Treasury data as of May 2022.

Assumption to distribute funds to each county: Funds are distributed on a pro-rata basis to each county based on the share of the population of each non-metropolitan city within each county.

Elementary and Secondary School Emergency Relief Fund = $98.1 billion

Allocation formula: ARP funding for school districts (i.e., local educational agencies) was allocated to states based in proportion to the amount each state received under Tile I, Part A of the Elementary and Secondary Education Act in fiscal year 2020. Title I grants are distributed under four types of formulas – Basic Grant Formula, Concentration Grant Formula, Targeted Grant Formula, and Educational Incentive Grant Formula. Each one of these grants distributes funds based, in part, on the population of children within the school district who live in households with incomes below the poverty line, live in institutions for neglected or delinquent children, or live in families receiving Temporary Assistance for Needy Families.[31] Under ARP, states had to distribute at least 90 percent of the funds to school districts.

Data on allocations: Top-line expenditure number from the ARP.

Assumption to distribute funds to each county: 90 percent of the total allocation is allocated to school districts based on their FY 2020 share of the total Title I funds as reported by the Department of Education. We use the estimated FY 2020 ESEA Title I allocations available at: https://www2.ed.gov/about/overview/budget/titlei/fy20/index.html. The funds are then distributed to census tracts based on the share of the population residing within the census tract that also resides within the school district.

[31] For more detail see CRS R47702: "ESEA Title I-A Formulas: A Primer."

Child Tax Credit (ARP Increase) = $88.9 billion

Allocation formula: The ARP increased the value of the Child Tax Credit (CTC) from $2,000 to $3,600 for each child under age 6 and from $2,000 to $3,000 for each child between the ages of 6 and 16. The ARP expansion allowed 17-year-olds to qualify for the CTC. The ARP expansion also made the CTC fully refundable, benefiting those taxpayers who had little or no income. Finally, the ARP delivered half of the CTC in monthly payments between July and December 2021.

Data on allocations: The Office of Tax Analysis (OTA), in response to a request by the Office of Economic Policy, prepared and provided the total differential within each county between the amount taxpayers within the county would have received under pre-ARP law and the amount the taxpayers within the county actually received under ARP.

Assumption to distribute funds to each county: None. We use the actual observed spending amount as provided by OTA.

Childcare Funds = $37.3 billion

Allocation formula: The childcare funds were distributed under two programs – the Child Care Development Fund (CCDF) and the Child Care Stabilization Fund (CCSF). Both funds were allocated to the states based the number of children under age 5, the number of children qualifying for the school lunch program, and per capita income. CCDF funds are provided either directly to lower income families with children using childcare services or directly to service providers. CCSF funds were distributed to childcare providers and could be used for various business expenses.

Data on allocations: https://www.whitehouse.gov/briefing-room/statements-releases/2021/04/15/fact-sheet-biden-harris-administration-announces-american-rescue-plan-funding-to-rescue-the-child-care-industry-so-the-economy-can-recover/.

Assumption to distribute funds to each county: Funds are distributed across each county within the state based on the county's share of the state's total population of children under the age of 5.

Pandemic Electronic Benefit Transfer (P-EBT) = $36.9 billion

Allocation formula: For children whose school or childcare facility was closed or experienced a reduction in person instruction, P-EBT provided eligible children with EBT benefits (i.e., funds to be used for food). In addition to having a school closure or reduced in person instruction, children ages 6 or older had to be eligible for free or reduced lunch, which typically requires living in a household with income less than 185 percent of the federal poverty line.

Data on allocations: Data from April 2021 through September 2022 available at https://www.fns.usda.gov/sites/default/files/resource-files/snap-pebt-2.xlsx.

Assumption to distribute funds to each county: Funds are distributed across each county within the state based on the county's share of the state's total population of children under age 18 living in household with incomes below the poverty line.

Higher Education Emergency Relief Fund = $35.2 billion

Allocation formula: ARP funding for public and private nonprofit colleges (i.e., institutions of higher education) was distributed to colleges based on the following formula:

- 75 percent of funds were allocated based on each college's share of the total enrollment of Pell Grant recipients who were not exclusively enrolled in distance education courses in the academic year 2018-2019;

- 23 percent of funds were allocated based on each college's share of the total enrollment of non-Pell Grant recipients who were not exclusively enrolled in distance education courses in the academic year 2018-2019; and

- 2 percent of the funds were allocated based on each college's share of the total enrollment of Pell Grant recipients who were exclusively enrolled in distance education courses in the academic year 2018-2019.

Pell Grant recipients tend to be students with limited resources. In school year 2021-2022, 96 percent of all Pell Grant recipients had family incomes no more than $70,000, and about 45 percent had incomes no more than $20,000.[32]

Data on allocations: https://www2.ed.gov/about/offices/list/ope/arpa1allocationtable.pdf.

Assumption to distribute funds to each county: We identify the location of the college by OPEID and assign the colleges to the relevant census tract. We then aggregate to the county level and assign the funds to the relevant county.

Restaurant Revitalization Fund = $28.4 billion

Allocation formula: According to Small Business Administration (SBA), restaurants, food stands, food trucks, caterers, bars, bakeries, breweries, and other establishments that provided in-person food or drink services that constituted at least a third of gross receipts could apply for funding.[33] SBA could provide between a $1,000 and $5 million to eligible businesses.

[32] Authors' calculation using data from Table 3A of the Pell Grant End-of-Year Reports for Award Year 2021-2022, available at https://studentaid.gov/sites/default/files/fsawg/datacenter/library/2021-2022-Pell-EOY-Tables.zip.
[33] See https://www.sba.gov/funding-programs/loans/covid-19-relief-options/restaurant-revitalization-fund for more detail.

Data on allocations: Funds provided to each business are available at https://data.sba.gov/dataset/rrf-foia. Data were geocoded using the Census Geocoder.

Assumption to distribute funds to each county: None. We use the actual county of the spending.

Emergency Rental Assistance = $21.2 billion

Allocation formula: ERA funds were distributed under two formulas:

- Per-capita formula: $18.7 billion was distributed to state was allocated a total ERA allocation based on the population of the state and subject to a minimum, such that no state could receive less than $152 million. If a local government within the state elected to receive funding, it received 49 percent of its per capita amount of the state's total allocation and that amount was subtracted from the amount payable to the state.

- High-need formula: $2.5 billion was distributed to state and local governments based on the number of very low-income renter households paying more than 50 percent of income on rent or living in substandard or overcrowded conditions, rental market costs, and change in employment since February 2020. Not all state and local governments received a high-need allocation.

Data on allocations: https://home.treasury.gov/system/files/136/ERA2_Allocations_Eligible_Entities_572021.pdf.

Assumption to distribute funds to each county: Per-capita formula funds are distributed pro-rata to each county based on the county's share of the total renting population. High-need formula funds are first assigned to their local government, then distributed across the local government based on the share of the renting population.

Shuttered Venue Operators Grant = $14.5 billion

Allocation formula: Grants were provided directly from the Small Business Association (SBA) to live venue operators or promoters, theatrical producers, live performing arts organization operators, museum operators, movie theater operators, and talent representatives such that each grantee received approximately half a year of gross earned revenue. The grant amounts could not exceed $10 million. See https://www.sba.gov/funding-programs/loans/covid-19-relief-options/shuttered-venue-operators-grant/about-svog#id-eligibility for more detail.

Data on allocations: Funds provided to each business are available at https://data.sba.gov/dataset/svog. Data were geocoded using the Census Geocoder.

Assumption to distribute funds to each county: None. We use the actual county of spending.

<u>School Testing = $9.9 billion</u>

Allocation formula: The Centers for Disease Control and Prevention (CDC) provided allocations to states through a population-based formula.

Data on allocations: https://public3.pagefreezer.com/browse/HHS.gov/30-12-2021T15:27/https://www.hhs.gov/about/news/2021/03/17/biden-administration-invest-more-than-12-billion-expand-covid-19-testing.html.

Assumption to distribute funds to each county: Allocations were distributed across counties based on each county's share of the state's population between the ages of 5 and 17.

<u>Child and Dependent Care Tax Credit (ARP Increase) = $9.8 billion</u>

Allocation formula: The ARP increased the value of the Child and Dependent Care Tax Credit (CDCTC) by: (1) making the credit refundable; (2) increasing the cap on expenses, and (3) raising the credit rate for the lowest income taxpayers and phasing out the credit for high income taxpayers.[34]

Data on allocations: The Office of Tax Analysis (OTA), in response to a request by the Office of Economic Policy, prepared and provided the total differential within each county between the amount taxpayers within the county would have received under pre-ARP law and the amount the taxpayers within the county actually received under ARP.

Assumption to distribute funds to each county: None. We use the actual observed spending amount as provided by OTA.

<u>Earned Income Tax Credit (ARP Increase) = $9.6 billion</u>

Allocation formula: The ARP expanded the value of the Earned Income Tax Credit (EITC) for childless taxpayers by (1) increasing the phase-in percent from 7.65 percent to 15.3 percent, meaning every additional dollar earned increased the value of the EITC by about $0.08; (2) increased the value of the credit from $543 to $1,502; and (3) phased-out the credit beginning at $11,600 rather than $8,800 for single taxpayers and $17,500 rather than $14,280 for married taxpayers.[35]

Data on allocations: The Office of Tax Analysis (OTA), in response to a request by the Office of Economic Policy, prepared and provided the total differential within each county between the amount taxpayers within the county would have received under pre-ARP law and the amount the taxpayers within the county actually received under ARP.

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[34] For more detail, see CRS Insight IN11645.
[35] For more detail, see CRS Insight IN11610.

Assumption to distribute funds to each county: None. We use the actual observed spending amount as provided by OTA.

Capital Projects Fund = $9.6 billion

Allocation formula: Grants to states under the Capital Projects Fund were distributed to states as follows: each state received (1) a distribution of $100 million and (2) a distribution based on a formula that accounted for each state's total population share, each state's share of the total population in poverty, and each state's share of the total rural population.

Data on allocations: Allocations are available at: https://home.treasury.gov/system/files/136/Allocations-States.pdf.

Assumption to distribute funds to each county: Funds were distributed across states based on the share of the population.

Homeowners Assistance Fund = $9.3 billion

Allocation formula: Funds were allocated to states based on the number of unemployed individuals within the state during the last four months of 2020 and the number of mortgages more than 30 days past due during the fourth quarter of 2020. The allocation formula distributed 25 percent of the funds based on the state's unemployment share and 75 percent of the funds based on the state's mortgages more than 30 days past due share.

Data on allocations: Allocations are available at: https://home.treasury.gov/system/files/136/HAF-state-territory-data-and-allocations.pdf.

Assumption to distribute funds to each county: Funds were distributed across states based on the share of the households with a mortgage within each county.

State Small Business Credit Initiative = $8.0 billion

Allocation formula: Funds were allocated to states based on each state's share of the total employment decline from December 2019 to December 2020 subject to a minimum.

Data on allocations: Allocations are available at: https://home.treasury.gov/system/files/256/Updated-Preliminary-Allocations-Table-Nov-2021.pdf.

Assumption to distribute funds to each county: Funds are distributed to each county based on the county's pro-rata share of the total state population.

15% SNAP Benefit Increase = $6.7 billion

Allocation formula: Temporarily increased the maximum SNAP benefit by 15 percent through September 2021. According to the Department of Agriculture, the increase provided about $27 more per person.[36]

Data on allocations: Data on number of SNAP recipients from April 2021 through September 2021 available at https://www.fns.usda.gov/sites/default/files/resource-files/snap-4fymonthly-2.xlsx. We assume every participant experienced a $27 increase in benefits.

Assumption to distribute funds to each county: Funds are distributed across each county within the state based on the county's share of the state's total population of households receiving SNAP or cash assistance.

Community Health Centers = $6.0 billion

Allocation formula: Provided grants to community health centers to offset the effects of the pandemic.

Data on allocations: https://bphc.hrsa.gov/funding/coronavirus-related-funding/fy-2021-american-rescue-plan-funding-health-centers-h8f/awards.

Assumption to distribute funds to each county: Funds are distributed to the county in which the Community Health Center is located.

Low Income Home Energy Assistant Program = $4.4 billion

Allocation formula: Low Income Home Energy Assistance Program (LIHEAP) funds are distributed to states based on each state's share of low-income household expenditures on home energy. LIHEAP is available to households with less than 150 percent of the poverty threshold or 60 percent of the state median income.

Data on allocations: https://www.hhs.gov/about/news/2022/04/21/hhs-awards-over-385-million-help-households-lower-cooling-and-heating-costs.html#footnoteii_i8w70dp.

Assumption to distribute funds to each county: Funds are distributed across each county within the state based on the county's share of the state's total population of living in households with no more than 150 percent of the poverty threshold.

[36] https://www.usda.gov/media/press-releases/2021/03/22/usda-increases-snap-benefits-15-funding-american-rescue-plan.

Substance Abuse and Mental Health Service Administration Grants = $2.9 billion

Allocation formula: Allocated in proportion to the Substance Abuse and Mental Health Services Administration block grant.

Data on allocations: https://www.samhsa.gov/sites/default/files/fy21-american-rescue-plan.pdf.

Assumption to distribute funds to each county: Funds are distributed across each county within the state based on the county's share of the state's total population.

Individuals with Disabilities Education Act Grants = $2.9 billion

Allocation formula: Funds are allocated based on the proportion of children with special needs.

Data on allocations: https://www2.ed.gov/policy/speced/leg/arp/arp-idea-allocations.html.

Assumption to distribute funds to each county: Allocations were distributed across counties based on each county's share of the state's population with disabilities under age 18.

Emergency Assistance to Non-Public Schools = $2.6 billion

Allocation formula: Funds were allocated based on each state's relative share of the total number of children aged 5 through 17 enrolled in non-public schools residing in families with incomes at or below 185 percent of the poverty line.

Data on allocations: https://oese.ed.gov/arp-eans-awards/.

Assumption to distribute funds to each county: Allocations were distributed across counties based on each county's share of the state's population of individuals ages 5 to 17.

Historically Black Colleges and Universities = $1.6 billion

Allocation formula: Funding was distributed to colleges based in part on each Historically Black Colleges and Universities (HBCU) share of the total Pell Grant recipients in HBCUs.

Data on allocations: https://www2.ed.gov/about/offices/list/ope/arpa2hbcuallocationtable.pdf.

Assumption to distribute funds to each county: We identify the location of the college by OPEID and assign the colleges to the relevant census tract. We then aggregate to the county level and assign the funds to the relevant county.

Local Assistance and Tribal Consistency Fund = $1.5 billion

Allocation formula: Funds were allocated on the basis of poverty rates, household income, land values, unemployment rates, and child poverty for the 20-year period ending with September 30, 2021. Allocations are subject to a maximum of $6 million, a minimum of $50,000, and a per capita maximum of $300. (Tribal allocations are not publicly available and not included.)

Data on allocations: Allocations are available at: https://home.treasury.gov/system/files/136/LATCF-Allocations-for-Eligible-Revenue-Sharing-County-Governments.pdf and https://home.treasury.gov/system/files/136/Local-Assistance-Tribal-Consistency-Fund-Allocations-Eligible-Revenue-Sharing-Consolidated-Governments.pdf. Tribal allocations are not publicly available and not included.

Assumption to distribute funds to each county: None, funds are distributed counties. Tribal funds are not included as they are not publicly available.

Older Americans Act Grants = $1.4 billion

Allocation formula: Funds are distributed to states, in part, based on the number of people older than age 60.

Data on allocations: Allocations are available at: https://acl.gov/sites/default/files/about-acl/2021-05/FY%202021%20ARP%206%20Programs%204-30-21%20Values%20Only%20version%202.pdf.

Assumption to distribute funds to each county: Allocations were distributed across counties based on each county's share of the state's population of individuals ages 65 and older.

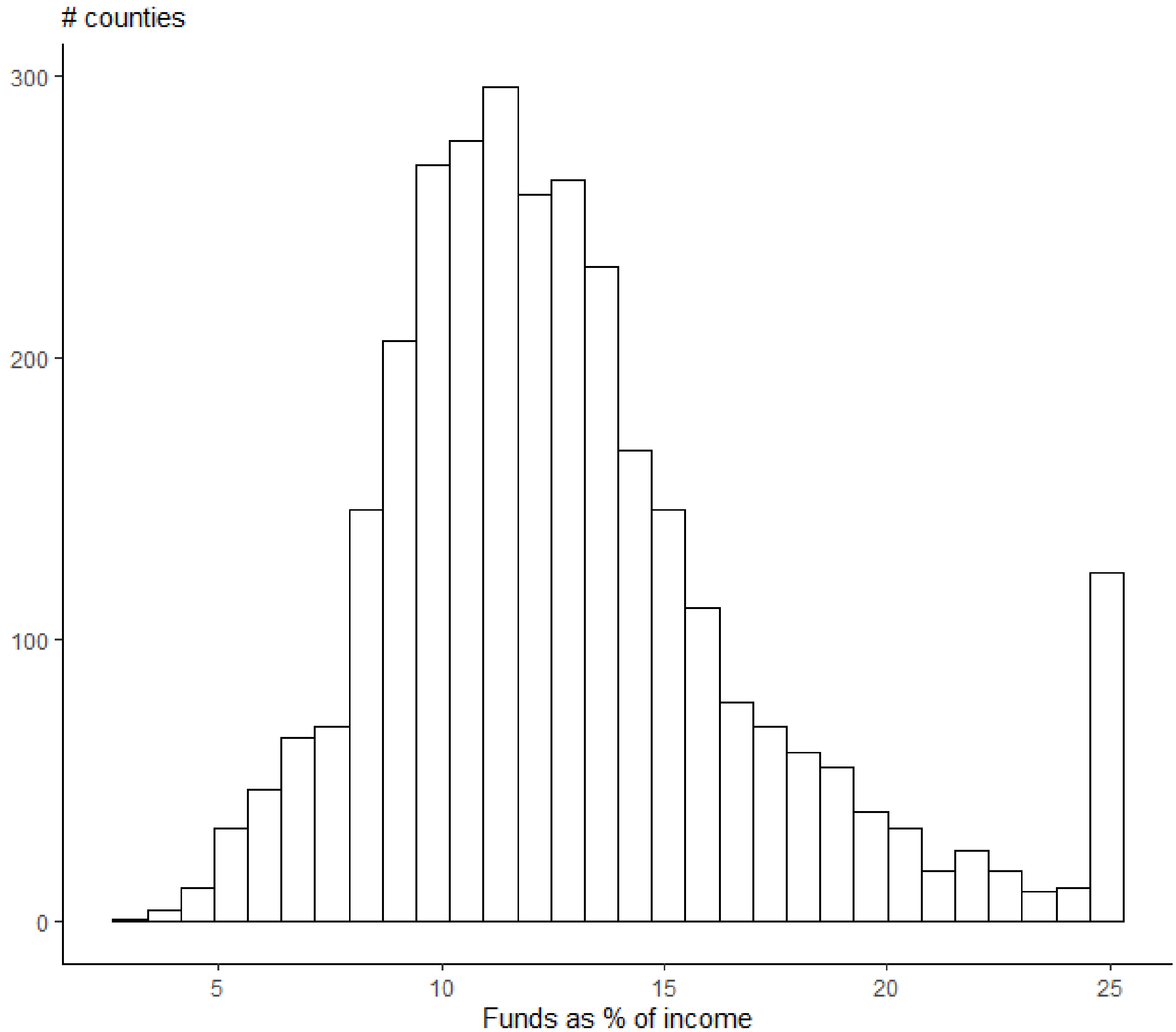
Build Back Better Challenge Grants = $1.0 billion

Allocation formula: Funds are awarded on a competitive basis to invest in regional areas.

Data on allocations: Awards are available at: https://www.eda.gov/news/press-release/2022/09/02/president-biden-announce-21-winners-1-billion-american-rescue-plan.

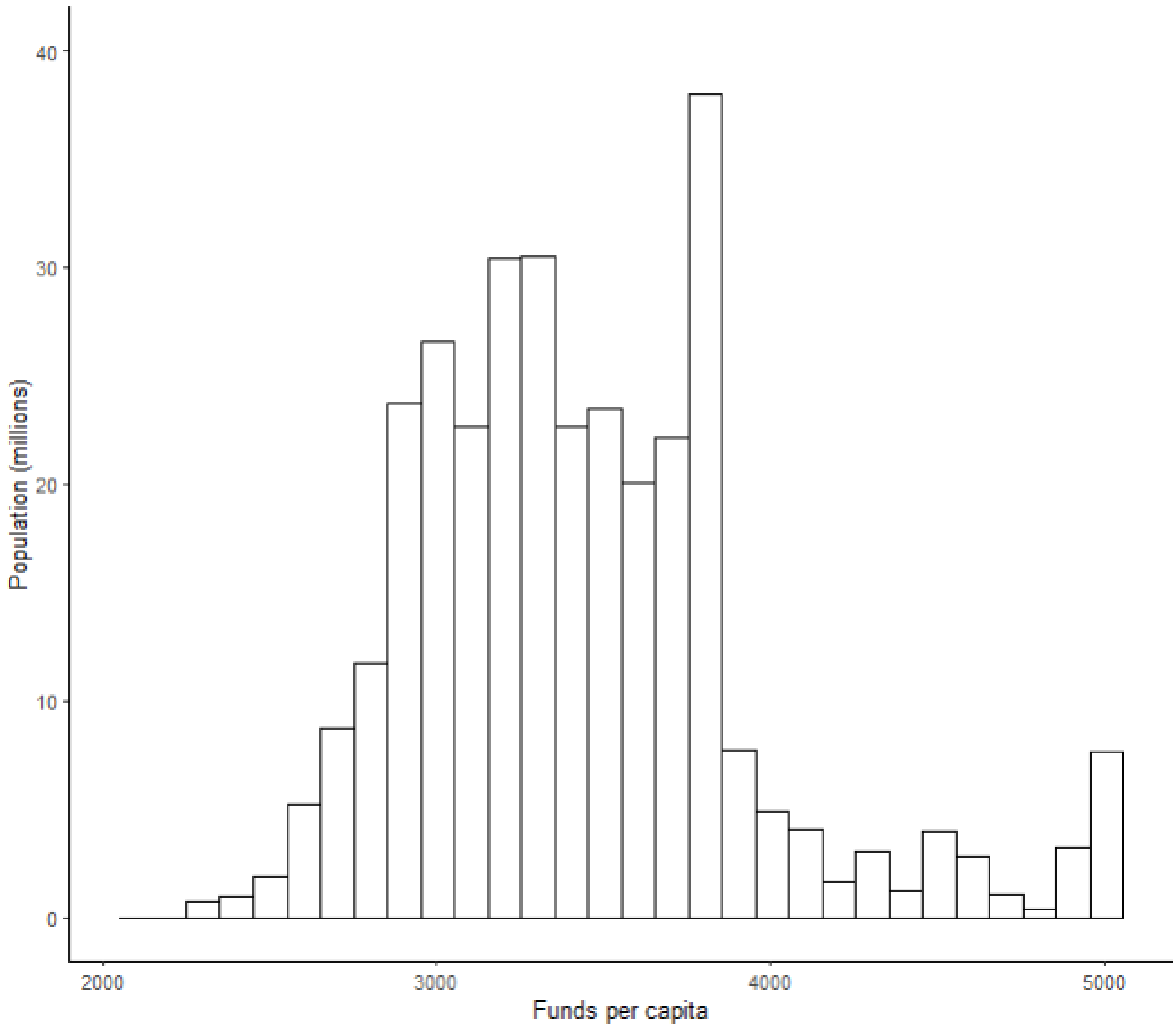
Assumption to distribute funds to each county: Allocations were distributed to the counties that included an awardee.

Figure A-1: Distribution of Funds as a Percent of Income Across Counties



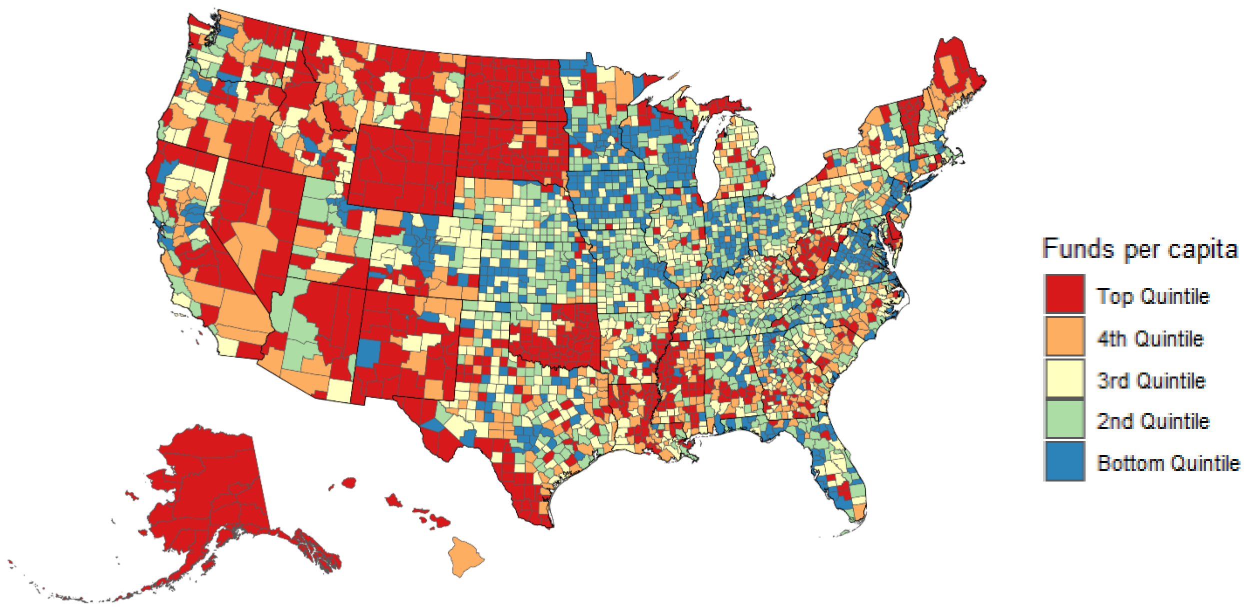
Note: Values above 25 percent are top-coded (119 counties, 1.1 percent of U.S. population, are top coded).

Figure A-2: Distribution of Funds per Capita Across Counties Weighted by Total County Population



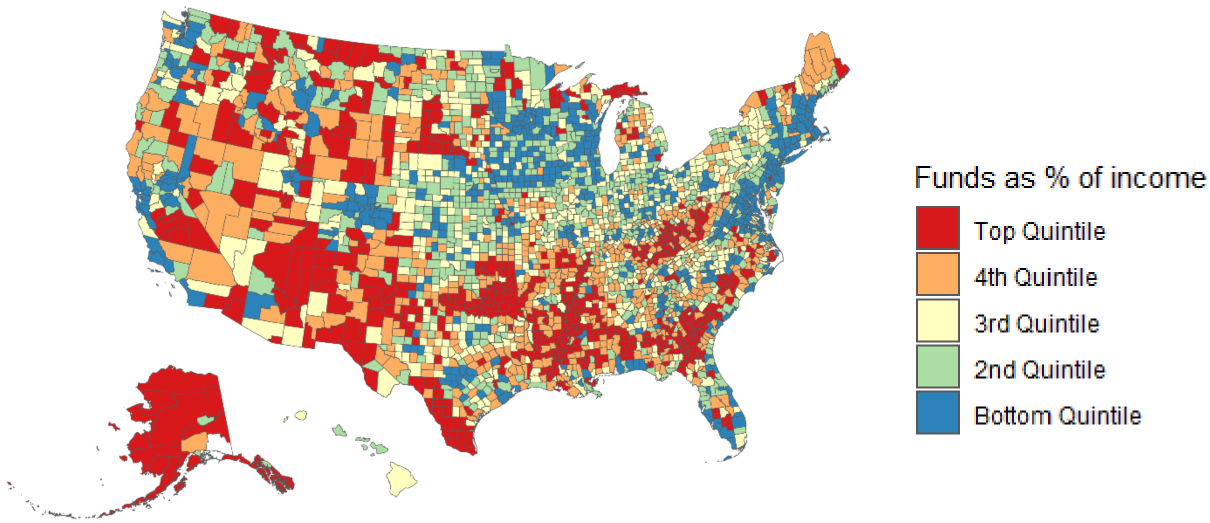
Note: Values above $5,000 per person are top coded (182 counties containing 2 percent of the population, are top coded).

Figure A-3: Funds per Capita Across U.S. Counties Weighted by Total County Population



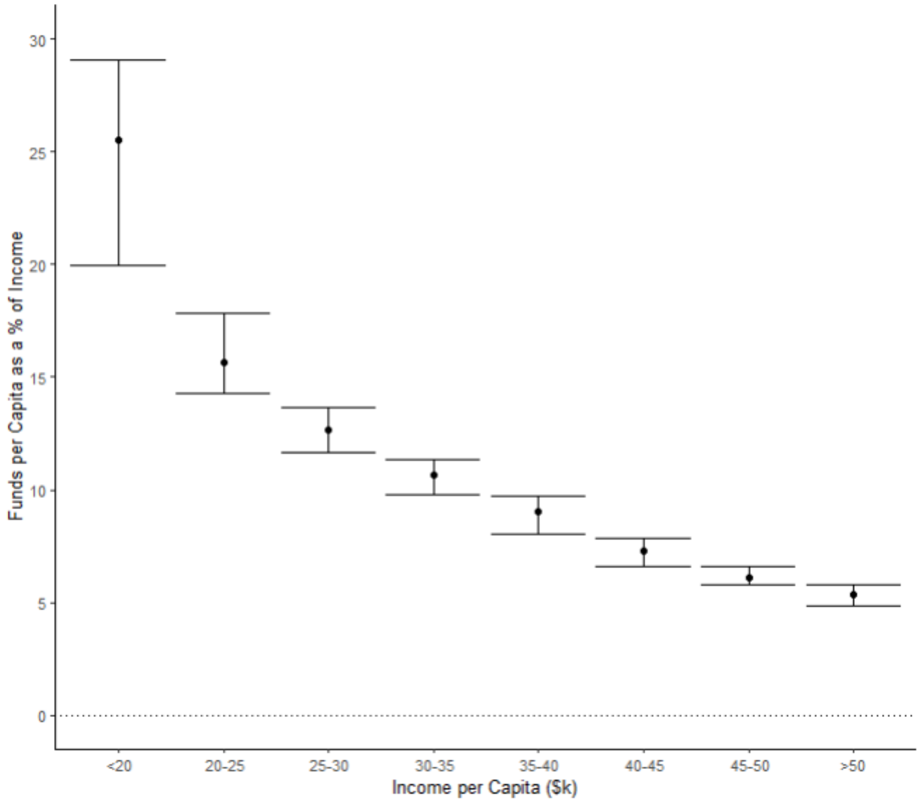
Note: Figure displays county-level per-capita allocations weighted by total county population

Figure A-4: Funds as a Percent of Income Across U.S. Counties



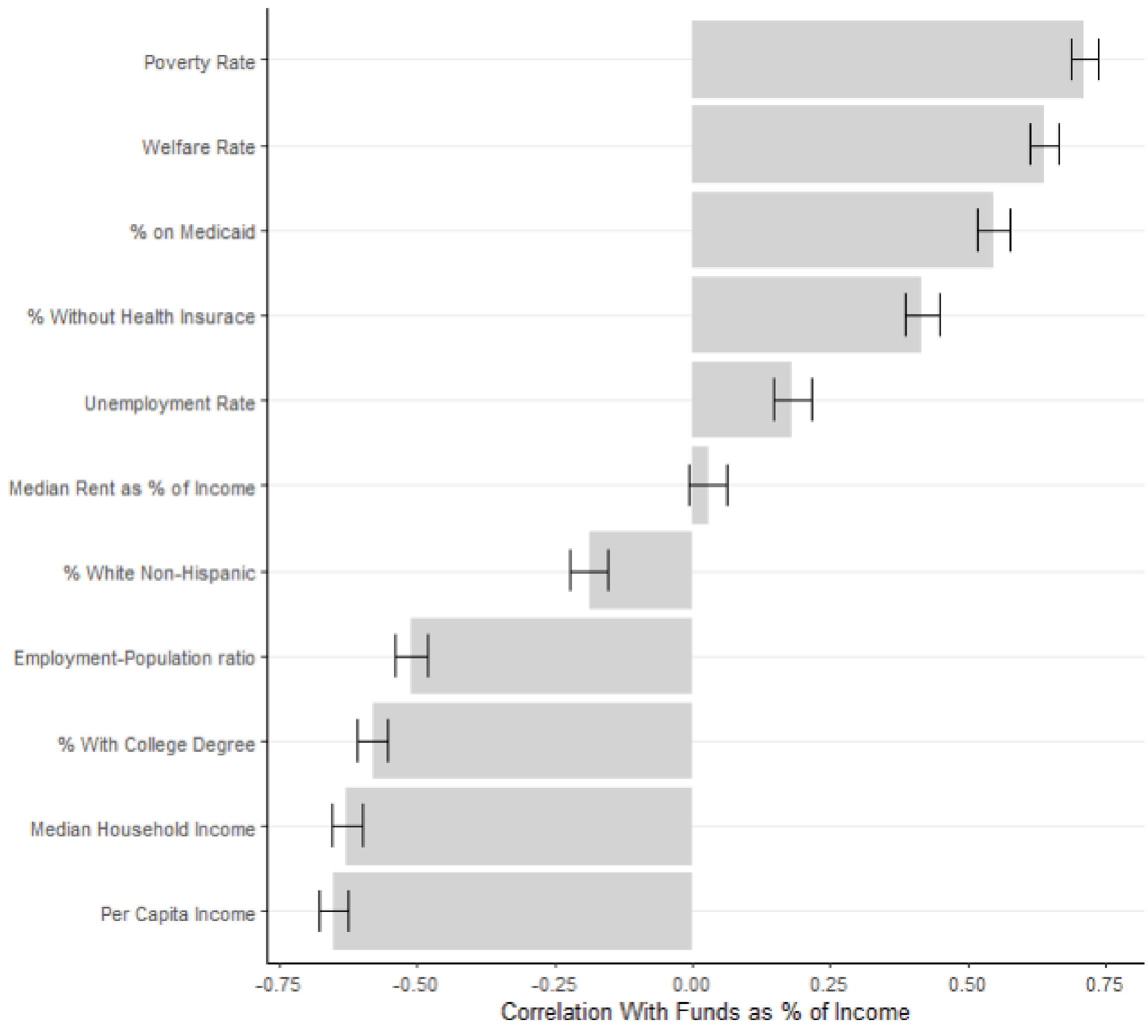
Note: Figure displays county-level per-capita allocations as a share of county income.

Figure A-5: Median and Interquartile Range (25th to 75th Percentile) of ARP Funds per Capita as a Share of Average County Income by County Income per Capita



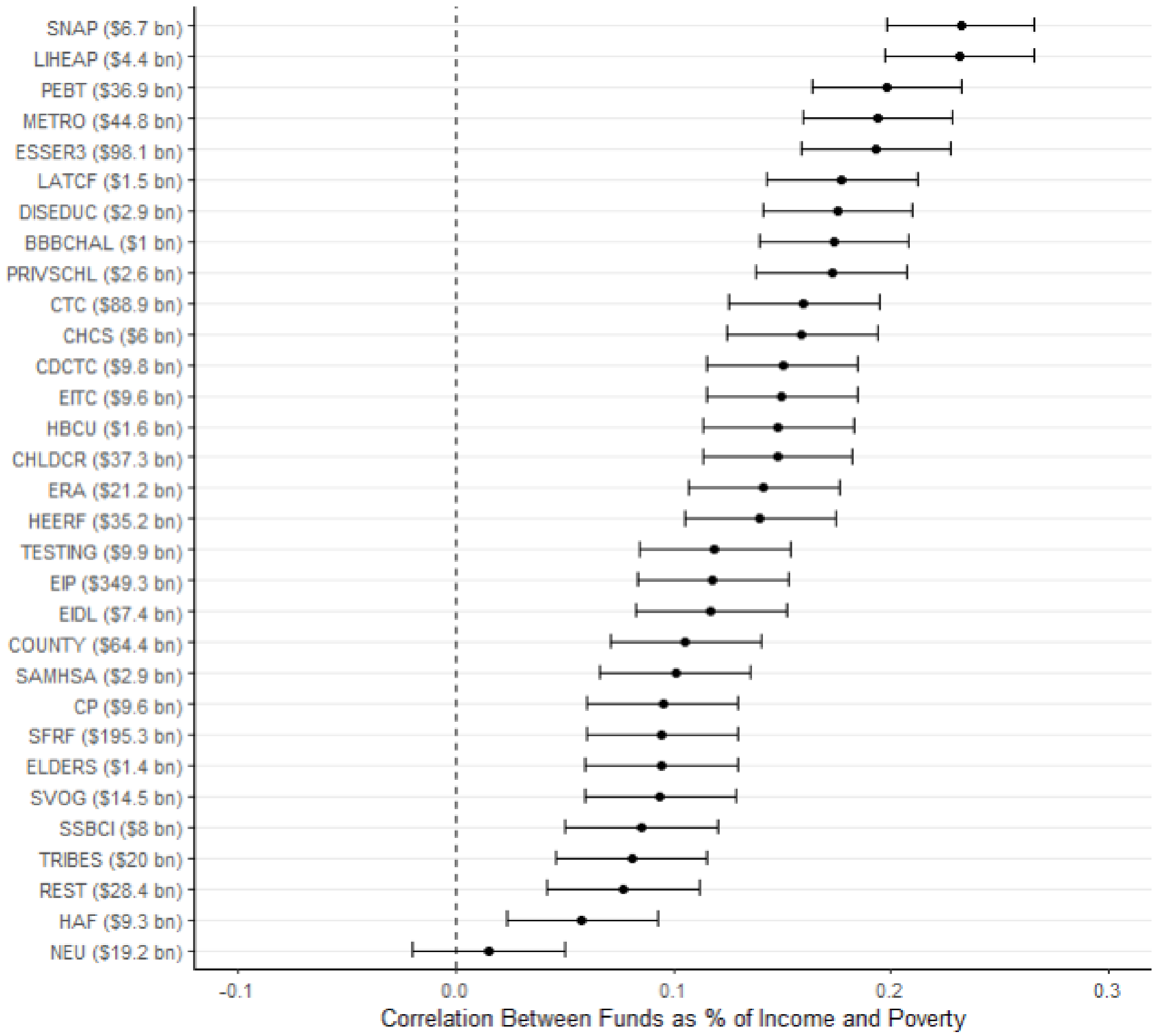
Notes: Dots show the median and the vertical bars the 25th and 75th percentiles of ARP funds per capita within $5,000 bins. All statistics are population weighted. Each income bin contains at least 25 counties.

Figure A-6: Correlation of County Demographics and Funds as a Percent of Income



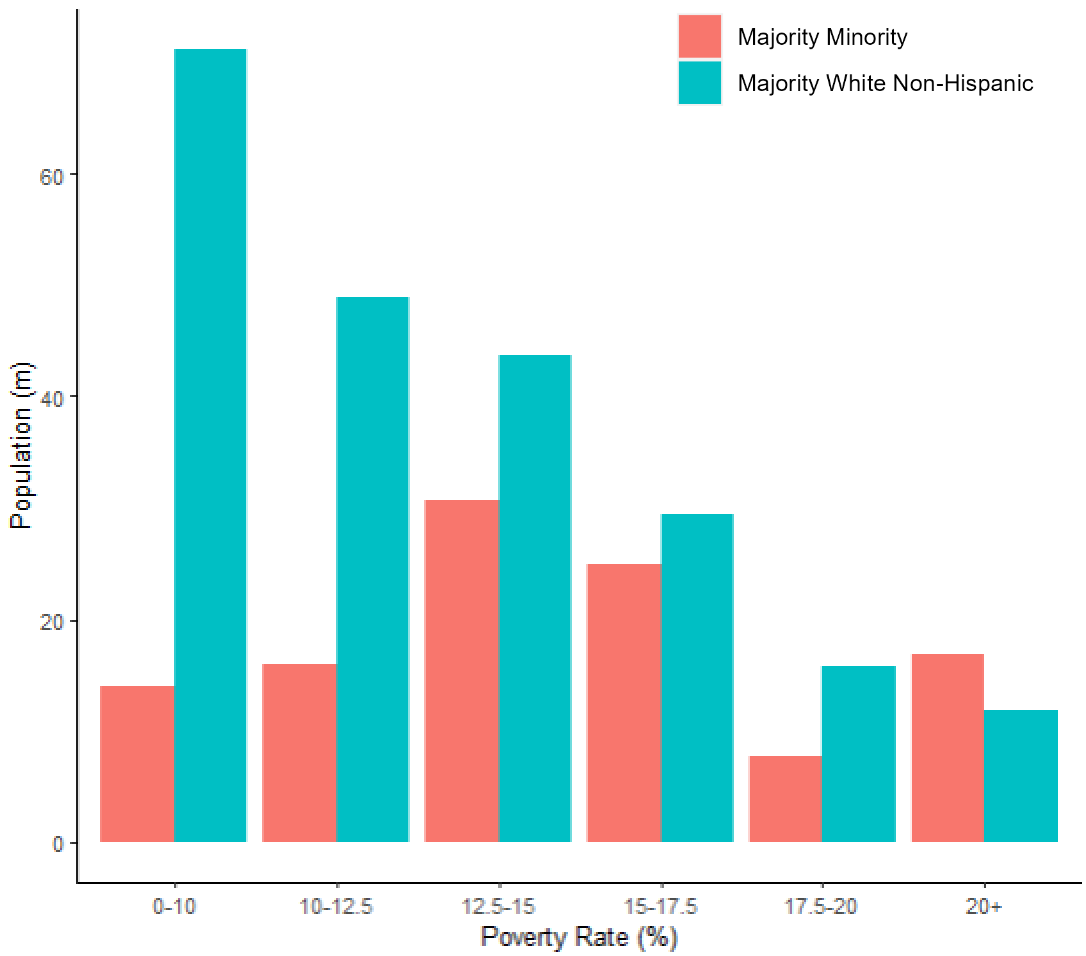
Note: All correlations are measured at the county level. Covariates are listed in descending order according to their correlation with ARP funds per capita. Bars represent 95 percent confidence intervals. Data on the unemployment rate are from the Bureau of Labor Statistics (BLS) Local Area Unemployment Statistics (LAUS). All specifications are population weighted.

Figure A-7: Correlation Between Poverty and Funds as a Percent of Income by ARP Program



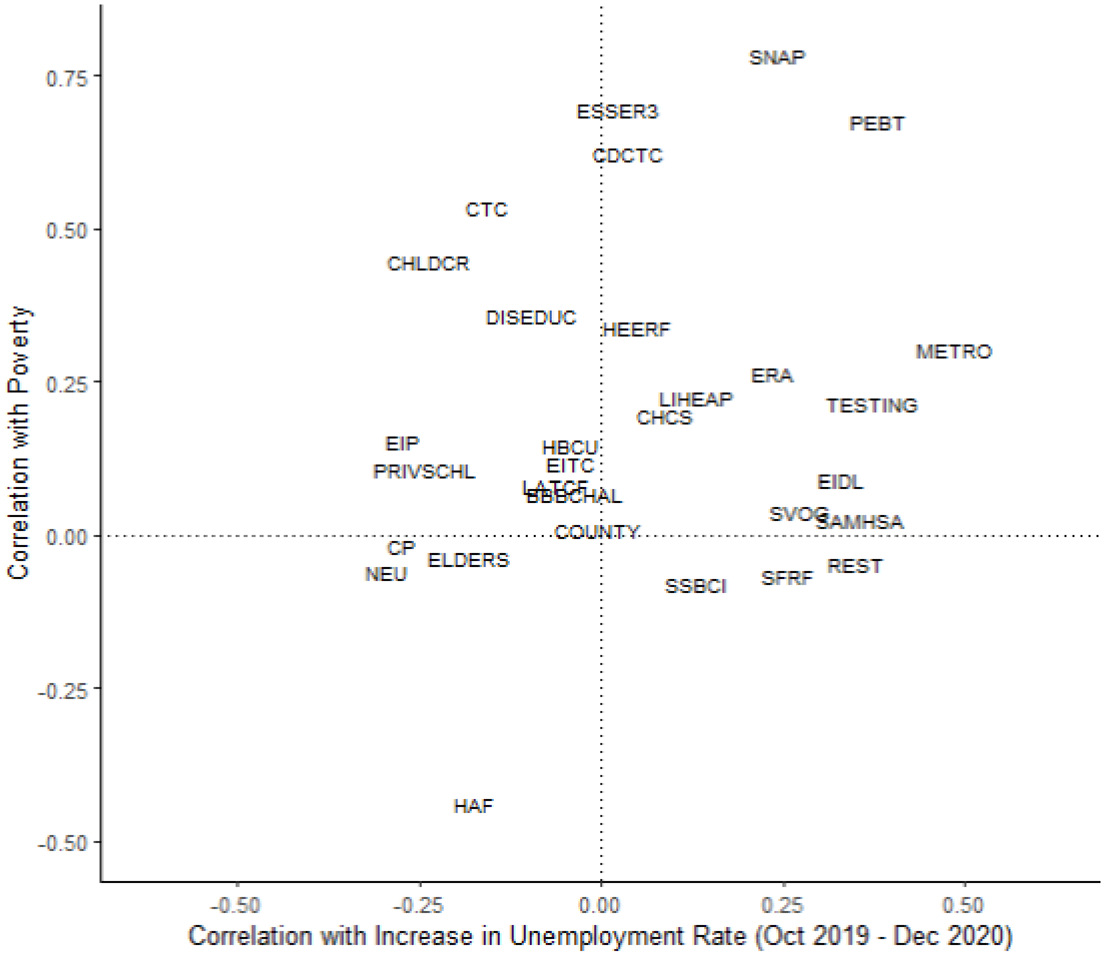
Note: Bars represent 95 percent confidence intervals. All specifications are population weighted.

Figure A-8: Population by Poverty and Whether a County is Majority Minority



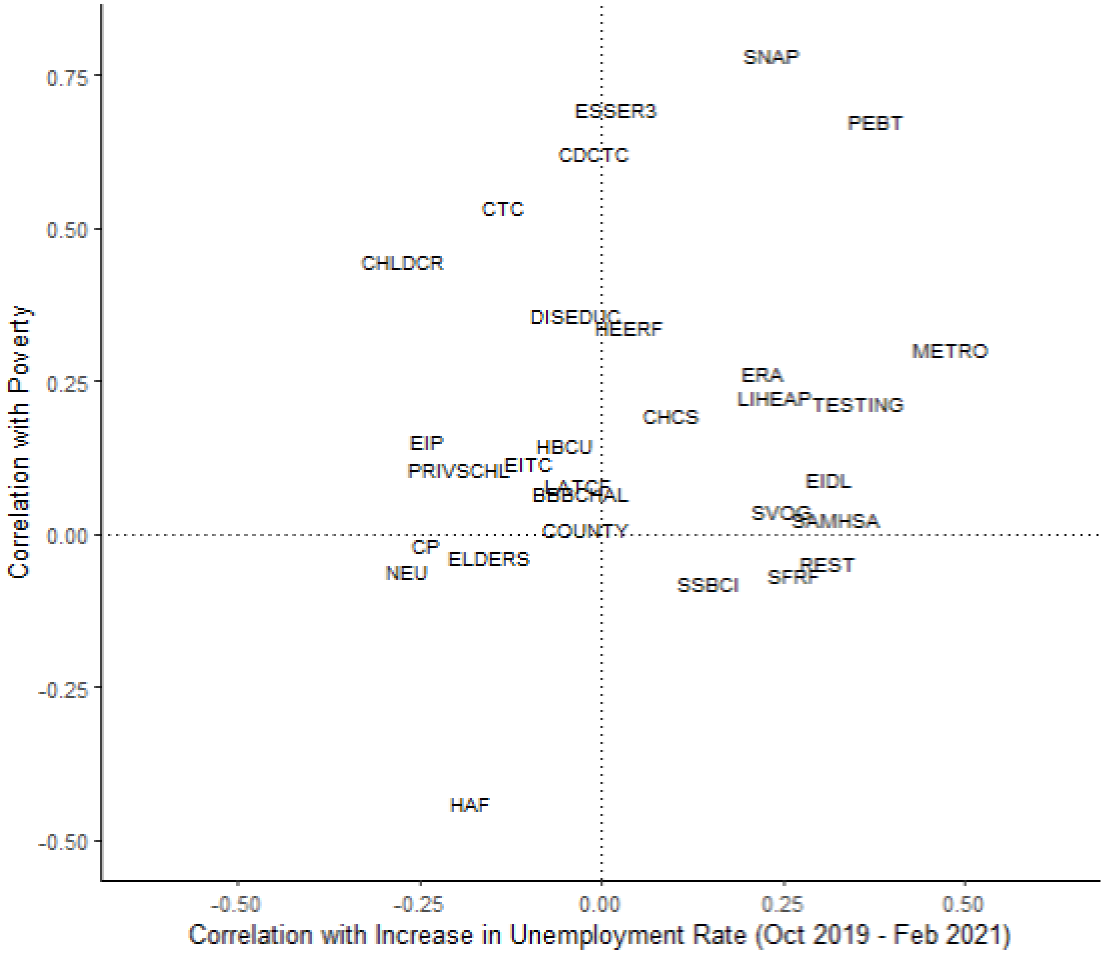
Note: Measured across counties.

Figure A-9: ARP Program Correlations with Poverty and Increases in the Unemployment Rate (October 2019 to December 2020)



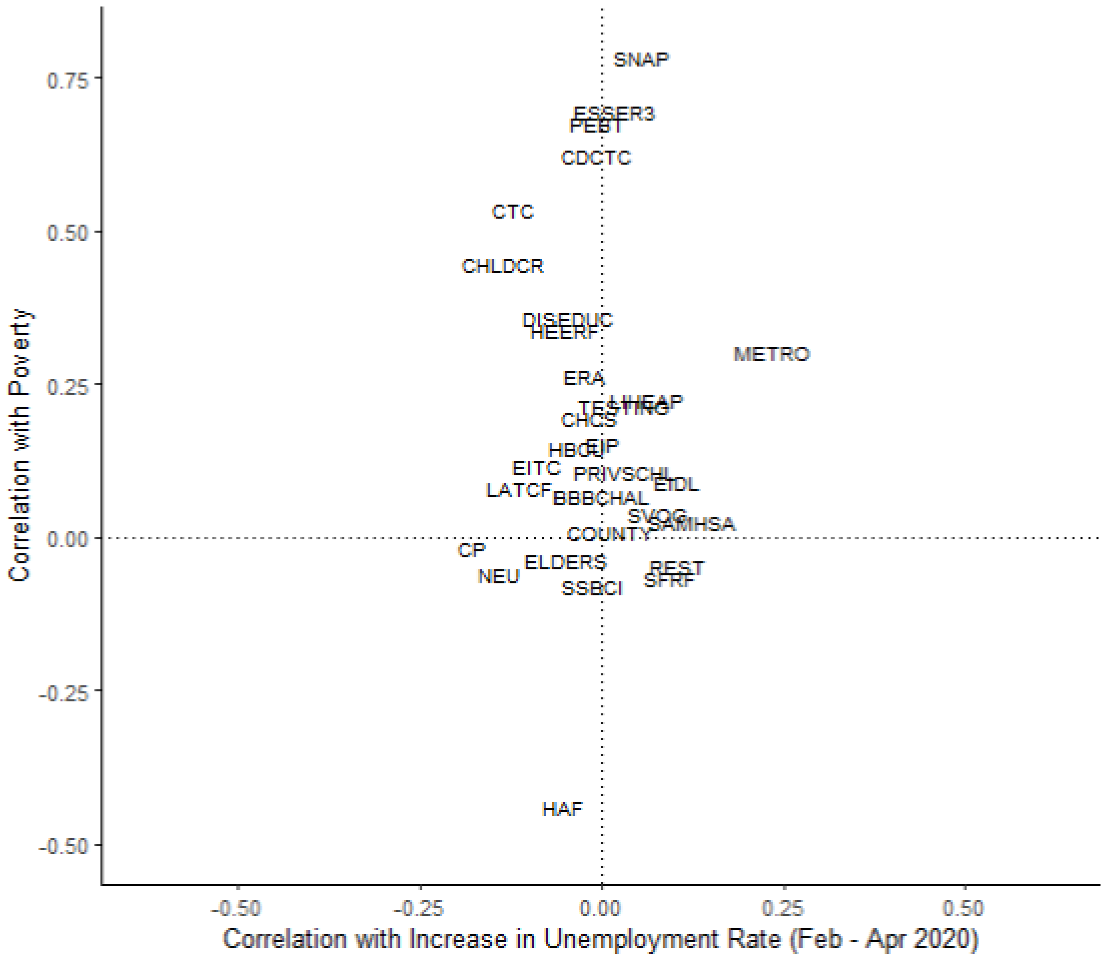
Note: Correlation calculated across counties. Increase in the unemployment rate is measured by country between October 2019 and December 2020. All specifications are population weighted.

Figure A-10: ARP Program Correlations with Poverty and Increases in the Unemployment Rate (October 2019 to February 2021)



Note: Correlation calculated across counties. Increase in the unemployment rate is measured by country between October 2019 and February 2021. All specifications are population weighted.

Figure A-11: ARP Program Correlations with Poverty and Increases in the Unemployment Rate (February 2020 to April 2020)



Note: Correlation calculated across counties. Increase in the unemployment rate is measured by country between February 2020 and April 2020. All specifications are population weighted.

Table A-1: Summary Statistics

	N	Mean	Standard Deviation	10th Percentile	Median	90th Percentile
ARP Funds Per Capita	3,143	3,700	2,000	2,900	3,300	4,400
ARP Funds as % of Income	3,141	14.4	11.3	8.7	12.5	19.4
Population	3,143	105,456	335,760	4,947	25,698	217,953
% White Non-Hispanic	3,141	76.3	20.2	45.2	83.8	95.3
Poverty Rate	3,141	15.1	6.3	8.1	14.2	23.3
Employment-Population Ratio	3,141	55.4	8.3	44.5	56.1	65.3
Per Capita Income	3,141	28,069	6,780	20,841	27,295	35,860
% Receiving Public Assistance	3,141	13.4	6.5	6.1	12.5	21.4
% With College Degree	3,141	22	9.6	12.5	19.6	34.8
% Without Health Insurance	3,141	10	5	4	9	16
% on Medicaid	3,141	17.6	7.5	8.9	16.7	27.4
Median Rent as % of Income	3,139	27.4	4.4	22	27.6	32.4

Note: Demographic variables from the 2015-2019 American Community Survey. Dollar amounts are reported in 2020 dollars. ARP Funds Per Capita are rounded to the nearest hundred.

Table A-2: Counties with Allocations above $5,000 per person

	Programs excluded from county funds		
	None	TRIBES	TRIBES ESSER3
Counties	182	68	18
Remaining counties	100.0%	37.4%	9.9%
Share of U.S. population	2.03%	1.23%	0.26%

Note: Counties included are those with allocations above $5,000 per person. TRIBES are funds distributed to tribal governments under the State Fiscal Recovery Fund. ESSER3 is the Elementary and Secondary School Emergency Relief Fund, which provided funding to school districts.

Table A-3: Funds per Capita by Poverty and Majority-Minority Status

	Poverty Rate					
	0-10	10-12.5	12.5-15	15-17.5	17.5-20	20+
Majority Minority	3,080	3,370	3,700	3,870	3,840	4,670
Majority White Non-Hispanic	2,980	3,280	3,430	3,590	3,690	3,810
Difference	100	90	270	280	150	860

Note: Measured across counties. Weighted by population by poverty rate and majority-minority status. Rounded to nearest 10. The total number of majority minority counties is 384 and the total number of majority white non-Hispanic majority counties is 2,757.

Table A-4: Relation Between State's Unemployment Rate, Racial Makeup, and Poverty

	Dependent variable:	
	Unemployment Rate	
	1	2
Percent White Non-Hispanic	-0.066***	-0.068***
	(0.012)	(0.012)
Poverty Rate		-0.074
		(0.083)
Observations	51	51
R^2	0.40	0.41

Note: The dependent variable is state unemployed population in 2020 Q4, seasonally adjusted, which was used by the State Fiscal Recovery Fund to allocate approximately 87 percent of the $195.3 billion. All specifications are population weighted. One, two, and three stars reflect statistical significance at the 10, 5, and 1 percent levels, respectively.

Table A-5: ARP Funds per Capita by County and the Unemployment Rate, Poverty and Race (Increase in the Unemployment Rate, October 2019 to December 2020)

Dependent Variable:	Percent Change in Funds per Capita			
Model:	(1)	(2)	(3)	(4)
Increase in Unemployment Rate	2.128***	1.281**	0.626	0.921
	(0.447)	(0.597)	(0.615)	(0.994)
Poverty Rate		2.082***	1.974***	2.232***
		(0.141)	(0.141)	(0.121)
Share White Non-Hispanic			-0.104***	
			(0.030)	
State Fixed Effects	No	No	No	Yes
Observations	3,140	3,140	3,140	3,140
R^2	0.06	0.46	0.47	0.68

Note: The dependent variable in each specification is 100 times the logarithm of funds per capita. Each observation is a county. All specifications are population weighted. Standard errors are clustered by state. One, two, and three stars reflect statistical significance at the 10, 5, and 1 percent levels, respectively.

Table A-6: ARP Funds per Capita by County and the Unemployment Rate, Poverty and Race (Increase in the Unemployment Rate, October 2019 to February 2021)

Dependent Variable:	Percent Change in Funds per Capita			
Model:	(1)	(2)	(3)	(4)
Increase in Unemployment Rate	2.266***	1.342*	0.758	0.888
	(0.563)	(0.701)	(0.705)	(1.039)
Poverty Rate		2.078***	1.965***	2.233***
		(0.141)	(0.140)	(0.122)
Share White Non-Hispanic			-0.105***	
			(0.030)	
State Fixed Effects	No	No	No	Yes
Observations	3,140	3,140	3,140	3,140
R^2	0.07	0.46	0.47	0.68

Note: The dependent variable in each specification is 100 times the logarithm of funds per capita. Each observation is a county. All specifications are population weighted. Standard errors are clustered by state. One, two, and three stars reflect statistical significance at the 10, 5, and 1 percent levels, respectively.

Table A-7: ARP Funds per Capita by County and the Unemployment Rate, Poverty and Race (Increase in the Unemployment Rate, February 2020 to April 2020)

Dependent Variable:	Percent Change in Funds per Capita			
Model:	(1)	(2)	(3)	(4)
Increase in Unemployment Rate	0.196	0.237	0.180	0.566***
	(0.213)	(0.182)	(0.171)	(0.169)
Poverty Rate		2.164***	1.972***	2.344***
		(0.133)	(0.134)	(0.136)
Share White Non-Hispanic			-0.134***	
			(0.030)	
State Fixed Effects	No	No	No	Yes
Observations	3,142	3,140	3,140	3,140
R^2	0.00	0.44	0.47	0.68

Note: The dependent variable in each specification is 100 times the logarithm of funds per capita. Each observation is a county. All specifications are population weighted. Standard errors are clustered by state. One, two, and three stars reflect statistical significance at the 10, 5, and 1 percent levels, respectively.

Table A-8: ARP Funds per Capita by County and Employment Change, Poverty and Race (Decrease in Employment, October 2019 to October 2020)

Dependent Variable:	Percent Change in Funds per Capita			
Model:	(1)	(2)	(3)	(4)
Decrease in Employment	2.45 X 10^-5***	1.85 X 10^-5***	7.65 X 10^-6**	1.66 X 10^-5***
	(5.97 X 10^-6)	(4.35 X 10^-6)	(3.32 X 10^-6)	(4 X 10^-6)
Poverty Rate		2.137***	1.982***	2.300***
		(0.133)	(0.137)	(0.140)
Share White Non-Hispanic			-0.118***	
			(0.035)	
State Fixed Effects	No	No	No	Yes
Observations	3,140	3,140	3,140	3,140
R^2	0.03	0.45	0.47	0.68

Note: The dependent variable in each specification is 100 times the logarithm of funds per capita. Each observation is a county. All specifications are population weighted. Standard errors are clustered by state. One, two, and three stars reflect statistical significance at the 10, 5, and 1 percent levels, respectively.