Distant Friends and Local Public Benefits: Social Spillover Effects from Out-of-State Medicaid Expansions

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Abstract

Understanding how individuals' social networks influence their interactions with public programs is important for policy design and evaluation. Public program participation often suffers from social frictions such as incomplete information and stigma. In this context, policy changes in one area could cause unanticipated indirect impacts in another, propagating through people's social networks as their friends experience the change. This paper studies social spillover effects arising from program changes in other states, and how they impact program take-up and support among populations not directly affected by the change. I focus on eligibility expansions in Medicaid, the United States' low-income public health insurance program, occurring during the 2010s. Comparing between communities within non-expansion states but with varying degrees of social connectedness to the expansion states, I find those with stronger social ties to the Medicaid expansions became more likely to enroll in the program following the expansions, even though eligibility was unaffected in their own state. The increase in Medicaid was reflected in decreases in uninsurance rates, suggesting the effect was driven by people becoming newly insured. I similarly find areas with stronger social connections to the expansions exhibited increased public support for Medicaid and the Affordable Care Act, and this effect was driven by higher income individuals who would not directly benefit from the program. The results highlight the potential indirect social impacts policy changes can have and underscore the policy consequences of our increasing social connectedness across geographic space.

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1 Introduction

Social networks are influential for many aspects of people's lives, yet when evaluating or designing public programs the role social networks could play is rarely considered. Understanding how programs interact with social networks is pivotal, as these interactions might amplify, mitigate, or otherwise modify the intended effects of the program, including on those not directly targeted by it. In the modern world, where social ties are not bound by geography thanks to improving communications technology, understanding such indirect social impacts is increasingly important—policy changes might cascade through networks in unexpected ways, potentially reaching individuals in varied locations and socioeconomic contexts. This paper explores how changes in public program eligibility ripple through social networks to affect individuals' interactions with and opinions about the program, even if they were not directly impacted by the policy change themselves.

To study how policies interact with social networks to create spillover effects, I examine the large state-level expansions in eligibility for Medicaid—the United States' low-income public health insurance option—which occurred in the 2010s as a result of the Affordable Care Act. The expansions lead to large increases in the number of Medicaid enrollees in the expansion states (Miller and Wherry, 2019). To isolate the social spillover effects of these eligibility changes, I study whether the expansions impacted how individuals interacted with and thought of the program in non-expansion states as a result of their out-of-state friends being exposed to the change. Understanding these potential spillover effects is important for evaluating and improving the operation of Medicaid—one of the largest public programs in the country in terms of spending and enrollment and a key ingredient for achieving universal health insurance coverage, which has remained distinctly illusive in the US.

The potential social spillover effects of expanded eligibility are not clear. Consider program take-up, which tends to be relatively low in the US (e.g., 44%–46% for Medicaid eligible adults in 2014–2017 (Decker et al., 2022)). Programs with more stringent eligibility criteria target populations with higher average needs, suggesting a higher take-up rate than programs with broader eligibility. However, in a context characterized by incomplete information and program stigma (Ko and Moffitt, 2022), this may not materialize as expected. Expanded eligibility criteria could mean that a larger portion of potential beneficiaries' social networks are either eligible or familiar with the program, potentially mitigating information barriers and reducing enrollment stigma due to the broader reach of the program within the community.

Furthermore, the social effects are not confined to those potentially eligible for the program; they might also permeate through to the broader population's approval of the program, which can, in turn, influence its future operation and sustainability. Theories of public program approval often depend on the perceived deservedness of beneficiaries (Gilens, 2000). More stringent criteria might correlate with higher approval, particularly for populations not typically viewed as deserving, by ensuring that only the 'truly needy' benefit. However, it's not clear that this is generally the case; the relationship between eligibility and approval likely hinges on the social construction of the beneficiary population and the nature of the benefits provided by the program. For example, healthcare might be perceived as a different kind of benefit compared to supplemental income, each carrying its own set of social and moral evaluations (Jensen and Petersen, 2017). The act of expanding eligibility also inherently alters the social construction of the program's beneficiaries. Including individuals with higher socioeconomic status (SES) might dilute the prevailing stereotypes and perceptions about the "typical" beneficiary.

To estimate these social effects, I compare communities with differential social network exposure to the Medicaid expansions in a difference-in-differences framework. I focus on the period 2012–2018, during which 22 states expanded Medicaid eligibility to cover all adults under 138% of the poverty line (it previously only covered children, pregnant women, parents, disabled, and elderly). I focus on communities (ZIP codes, counties, or Public Use Microdata Areas) within the 19 states that had not expanded Medicaid to all low-income adults as of 2018. Using the Facebook Social Connectedness Index (Bailey et al., 2018a) to measure social ties between communities, I estimate the effects of having more out-of-state friends exposed to a Medicaid expansion. The estimation strategy relies on the fact that, within a given non-expansion state, communities had varying degrees of baseline social connectedness to the expansion states and thus the expansions caused a varying shock to their social networks' exposure to the expansions. Comparing these communities over time and within the same state, I test whether those with relatively more friends in the expansion states also saw relatively higher take-up and support for Medicaid after the expansions. Identification comes from the relative differences in changes in take-up and support between communities within a non-expansion state, independent of the fixed characteristics of the community (e.g., urbanicity) and any time varying state-level differences (e.g., state policies, economic conditions).

Low-income adults in communities with stronger social connections to the Medicaid expanding states were more likely to enroll in Medicaid after the expansions—even though eligibility was largely unchanged for themselves—compared to communities in the same state but with less connection to the expansions. Specifically, I find that low-income non-elderly adults in Public Use Microdata Areas (PUMAs) with one standard deviation more friends per person in Medicaid expansion states were 0.8 percentage points more likely to be enrolled in Medicaid after the 2014 ACA expansions, a 4% increase from baseline. The impact on Medicaid enrollment was reflected in the uninsured rate (0.9 percentage point decrease) while the probability of being covered by other sources did not change, suggesting the results are driven by otherwise uninsured individuals becoming Medicaid covered.

In addition to the two-way fixed effects approach, I estimate impacts in an event study that compares communities with above vs. below median social exposure to the expansions. The event study confirms results are not driven by differential pre-trends, and I show it is robust to using methods from Callaway and Sant'Anna (2021) that address concerns resulting from the staggered adoption. In a second setting, I similarly estimate the impacts of California's early Medicaid expansion, which was rolled out at the county level beginning in 2011. Using ZIP code-level administrative monthly Medicaid enrollment counts, I find that ZIP codes in non-expansion counties with above median social connection on the counties expanding in 2011 experienced a 1-2% higher Medicaid enrollment following the expansion. These results add confidence that effects are not driven by reporting errors in survey data and generalize beyond the specific context of the 2014–16 expansions.

Next, I turn to examine effects on the public's policy preferences using data from the Cooperative Congressional Elections Study (CCES). Since 2012 the CCES has included a question about whether the respondent supports Congress repealing the ACA. Although not directly a question about Medicaid, expansion was one of the major and most prominent components of the legislation, and so overall support for the ACA is likely to be related to and affected by support for the Medicaid expansions. Using the county-level SCI and the same identification strategy as above, I find that counties with one standard deviation more friends per person in non-expansion states exhibited a 2 percentage point increase in support for the ACA. In a second specification I substitute ZIP code-level SCI instead of county and include county-year fixed effects to compare people within the same county but in ZIP codes with different degrees of social connection to Medicaid expansions; the effect remains strong with social connections proxied at the ZIP code level.

In a cross-sectional analysis I estimate the effects of changes in a ZIP codes number of friends per person exposed to Medicaid expansions. I find ZIP codes with one standard deviation higher social exposure were more likely to support their own state expanding Medicaid (4.6 percentage point increase) and increasing healthcare spending (2.2 percentage point increase), whereas I do not find a statistically significant difference in preferences for welfare spending. These results suggest the effects are driven by specifically healthcare related policy preferences.

In heterogeneity analyses, I find the effects on policy preferences are concentrated among higher income individuals rather than those who would most likely benefit from the policy change. I find those who would likely benefit (low-income childless adults) do not have different baseline preferences for the ACA and are not impacted by social exposure. These results suggest a role for the broader population of voters learning about the policy from their social network and changing opinions, which could have downstream impacts on the population that would benefit directly. It might also be that those likely to benefit are still not sufficiently informed to connect the survey questions about the ACA to Medicaid benefits, which requires an additional level of policy knowledge beyond awareness of the Medicaid program itself.

The results highlight the important dynamics of how geographically dispersed social networks can influence local public benefits participation, particularly in the digital age where social ties are not confined by physical proximity or boundaries. The findings suggest that policy changes in one jurisdiction can have ripple effects beyond its physical borders, influenced by the intricate web of social connections. Policymakers may need to recognize and account for these broader social influences when designing and implementing public programs. Considering such unforeseen spillovers can lead to more effective policy design and better-informed expectations about program outcomes.

1.1 Related Literature

The results contribute to a few strands of literature. First, I build on the literature on incomplete public benefits take-up and related barriers (Ko and Moffitt, 2022; Janssens and Van Mechelen, 2022; Moffitt, 1983; Heckman and Smith, 2004; Bhargava and Manoli, 2015; Aizer, 2003), in particular the role of social spillovers in program take-up (Bertrand et al., 2000; Aizer and Currie, 2004; Dahl et al., 2014b,a). Experimental evidence has found that interventions providing program information to potential beneficiaries can improve take-up (Bhargava and Manoli, 2015; Finkelstein and Notowidigdo, 2019). Social networks might help provide additional program information; most evidence focuses on very local social ties (e.g., neighbors), examining associations between individuals' own program behavior and the behavior of their local network (Bertrand et al., 2000; Aizer and Currie, 2004;

Chetty et al., 2013; Grossman and Khalil, 2020). It can be difficult to distinguish social network effects in this approach from other explanations such as endogenous sorting into neighborhoods or the effects of other correlated neighborhood characteristics. By examining the effects of a distant policy change that did not directly impact the study population, I isolate the social network impacts from these other potential explanations. Focusing on hyper-local networks also misses the growing importance of distant networks facilitated by communication technology, which are nearly as important but might operate differently from the impacts of local networks. I contribute to the limited evidence examining the effects of broader social networks (Dahl et al., 2014b; Wilson, 2022).

Chetty et al. (2013) find that people's neighborhood social networks can help overcome information frictions and assist them more optimally claiming the Earned Income Tax Credit (EITC). Wilson (2022) examines more distant online networks and finds social ties to state EITC programs might influence local EITC claiming behavior. It is not obvious that these results in the context of a tax-based income program with relatively higher take-up would be similar in Medicaid, an insurance program which requires application and renewal outside the tax system and may be subject to different types of information and stigma frictions. Moreover, these studies estimate impacts on how EITC recipients change their filing behavior but not on the extensive margin for whether they enroll in the first place.

A smaller literature related to program take-up has studied so-called "woodwork effects," where previously eligible individuals are induced to enroll in a program after eligibility expansions. Most of this evidence comes from Medicaid expansions (Frean et al., 2017; Sonier et al., 2013; Sacarny et al., 2022; Hudson and Moriya, 2017; Sommers et al., 2012). These studies tend to estimate the effects of a state expanding eligibility for a program on the behavior of the previously eligible in the same state (Anders and Rafkin, 2022). Researchers theorize this "woodwork effect" is driven by a combination of social network effects improving information or stigma frictions, but it is challenging to disentangle these social effects from other program changes that might otherwise reduce transaction costs for the previously eligible (e.g., through accompanying program operation changes), and more work is needed in this area (Sacarny et al., 2022). Since individuals in my study population are not directly impacted by the policy change, I argue my results are exclusively caused by social network effects, providing evidence that social networks add a distinct take-up effect independent from other program changes. Moreover, this evidence tends to come from estimating the impacts of having a parent become eligible for Medicaid on their previously eligible child's enrollment—I instead focus on adult peer networks, which might operate very differently than the effects of within-household eligibility changes. Finally, scant evidence has examined the apparent woodwork effect that occurred in the non-expansion states, and those that do touch on this subject come to conflicting findings on whether a woodwork effect occurred in the non-expansion states (Frean et al., 2017; Courtemanche et al., 2017). I fill this gap by providing evidence that a woodwork effect occurred in the non-expansion states, operating through social ties to the expansion states.

I also contribute to literatures related to the determinants of public program approval (Gilens, 2000; Jensen and Petersen, 2017; Nicholson-Crotty et al., 2021)and the diffusion of policies across geographies (Linos, 2013; Shipan and Volden, 2008; Gray, 1973; Walker, 1969; DellaVigna and Kim, 2022). DellaVigna and Kim (2022) study the evolution of polarization and policy diffusion in the US; they document that policy diffusion across states was best predicted by geographic proximity in 1950–2000, but since then political alignment has been the strongest predictor. These studies are limited in their ability to identify the policy experience of others as a causal impact on own policy preferences. An exception is Shigeoka and Watanabe (2023), who use quasi-randomization in neighboring election cycles in Japan to study the causal extent of policy diffusion and find neighboring jurisdictions are more likely to adopt similar policy. I contribute to this literature by providing causal evidence that the experience of one's geographically distant social network being exposed to a policy change influenced their own preferences about similar policies.

When considering how program eligibility impacts public approval for the program, the perceived deservedness of the beneficiaries usually key (Gilens, 2000). For example, Keiser and Miller (2020) find that, particularly among more conservative voters, information about higher administrative burdens in the TANF program increased public support. This relationship likely depends on the social construction of the beneficiary population (Nicholson-Crotty et al., 2021), and it's not clear that a health insurance program would have the same "deservedness" relationship as income-based programs (Jensen and Petersen, 2017). I add to this evidence by showing that expanding eligibility in Medicaid to a larger and higher income population increased support for the program.

Finally, my work contributes to a growing literature on the impacts of geographically distant social networks more generally, particularly for financial decisions (Kuchler and Stroebel, 2021). For example, Hu (2022) estimates the impact of being socially connected to distant flood events and finds it increases flood insurance purchases. And Bailey et al. (2018b) and Bailey et al. (2019) find changes in geographically distant housing markets impact people's house price expectations and purchasing decisions. I extend this work to include public program take-up and public approval as an economic behavior that can be influenced through social networks.

2 Institutional Background: Medicaid and the Affordable Care Act

Medicaid is the United State's public health insurance option for the poor. The program operates through a federal-state partnership administered at the state level under federal guidelines. The federal government provides matching funds to states running the program, which account for about half the program's costs. Income eligibility thresholds vary by state and by subgroup (e.g., children, pregnant women).[1]

Medicaid was established with the adoption of the Social Security Amendments of 1965,[2] in which the federal government provided matching funds to states to provide medical assistance to residents with insufficient resources to pay for their healthcare costs. State participation in the program was initially voluntary. By 1982, after Arkansas adopted Medicaid, all states were participating in the program.

Medicaid's general purpose is to be a source of health insurance for the low-income population, but there have historically been eligibility requirements in addition to income. The eligibility groups covered by Medicaid have evolved over the years and can generally be categorized into six subgroups of the low-income population: children, pregnant women, parents and caregivers, the disabled, the elderly (mostly in nursing homes), and non-disabled, childless adults. As the program has evolved eligibility has expanded to eventually cover all of these groups in some states, with non-disabled childless adults being the most recently expanding group.

Children have long been the largest subgroup of beneficiaries (Currie and Duque, 2019). This group began growing significantly in the late 1980s when states raised income eligibility limits for children and pregnant women. The passage of the Children's Health Insurance Program (CHIP) in 1998 expanded income eligibility limits further and lead to continued increases in the number of children covered.[3] By the mid-2000s nearly half of American

[1]The Kaiser Family Foundation publishes Medicaid income eligibility thresholds for major subgroups by state and year since the early 2000s https://www.kff.org/statedata/collection/trends-in-medicaid-income-eligibility-limits/.

[2]Medicaid is sometimes confused with Medicare, the public health insurance program for ages 65 and over, which was also created under the Social Security Amendments of 1965.

[3]Although Medicaid and CHIP are separate programs, states may bundle their administration and man-

children were eligible (Currie et al., 2008). Children continue to have higher income eligibility thresholds than most adult eligible categories.

Coverage of the elderly is much lower and has remained more stable. Most healthcare for the elderly is covered through *Medicare* rather than *Medicaid*. The main purpose of Medicaid coverage for the elderly is for nursing homes and long-term care. Typically, older Americans who have spent down their resources in later life will then become eligible for Medicaid, which now covers the majority of nursing home residents (Kaiser Family Foundation, 2017).

States are required to give Medicaid coverage to people who qualify for Supplemental Security Income, a program for individuals with low income and assets and who have a work-impairing disability. This is not to be confused with Social Security Disability Insurance, which is connected to one's work history and can grant access to Medicare.

For non-disabled adults, Medicaid coverage was historically reserved for parents and other caretakers with the exception of a few states. This changed, however, with the passage of the Affordable Care Act in 2010, described in detail below.

2.1 The ACA Medicaid Expansions

The Patient Protection and Affordable Care Act of 2010 (ACA) was enacted with the goal of reducing the number of uninsured Americans and improving access to care. A major provision of the ACA initially required states to expand Medicaid eligibility to all adults in families under 138% of the federal poverty line, which would grant new Medicaid eligibility to non-disabled, childless childless adults, who were for the most part previously excluded from eligibility in all but a few states. The costs of covering this new eligibility group were to be paid in full by the federal government with states gradually paying up to 10% of the cost by 2020. However, in 2012 the Supreme Court ruled in *National Federation of Independent Business v. Sebelius* that requiring states to expand their Medicaid programs was unconstitutional and thus states could choose whether to take the new eligibility expansion or maintain their previous eligibility and funding.

Figure 1 shows states' Medicaid expansion status as of 2018 (the last year in my study period), based on data from the Kaiser Family Foundation (Kaiser Family Foundation, 2023) and supplemented with additional state information. Most of the Southern states and many

agement and thus they are often considered as parts of the same broad program.

Midwestern states did not expand Medicaid. Figure 2 shows the growth in the number of states expanding Medicaid coverage to all low-income adults. Only four states had Medicaid programs that covered low-income non-disabled, childless adults before 2010. With the passage of the ACA, a few states expanded eligibility early before the primary role out in 2014, during which an additional 17 states expanded. Five additional states expanded in 2015 and 2016, after which there was a multi-year lull in major eligibility expansions. Since 2019, eight additional states expanded Medicaid, mostly through ballot initiatives rather than legislation (Brantley and Rosenbaum, 2021).

Figure 3 shows the trends in Medicaid enrollment in expansion states versus non-expansion states using American Community Survey data. There was a marked, approximately 20 percentage point increase in the proportion of low-income adults enrolled in Medicaid after 2014 in expansion states, which is not surprising given the large increase in the eligible population. However, there was also a smaller but meaningful increase in the non-expansion states, which might suggest spillover effects across state lines.

2.2 Medicaid Take-Up and the Woodwork Effect

Medicaid take-up has tended to be far bellow full enrollment, depending on the eligibility population. Kenney et al. (2012) estimated Medicaid participation rates in 2009 (before the ACA expansions) were 67% among eligible adults, 17 percentage points lower than for children. Sommers et al. (2012) similarly found an adult take-up rate of 63% in 2005–10, and was highest for disabled adults (76%) and lowest for childless adults (38%, though they were not eligible in most states at the time). Decker et al. (2022) modeled post-ACA adult Medicaid enrollment and estimated the take-up rate was 44%–46%. Moreover, they found the participation rate was similar in expansion and non-expansion states, contrary to estimates from before the ACA.

A number of studies have examined the potential barriers to Medicaid participation, including information frictions, stigma, and administrative burdens. Kenney et al. (2015) find that although awareness of Medicaid/CHIP for children was very high among low-income uninsured parents, only half were aware they were eligible. Aizer (2003) and Aizer (2007) finds community outreach efforts improved take-up in California, with information and administrative burdens being key barriers, especially among Hispanic and Asian Americans. Stigma has been suggested as a barrier to Medicaid take-up, but Stuber et al. (2000) and Stuber and Schlesinger (2006) have found it to be less important in Medicaid than other welfare programs. On the other hand, administrative burdens are a key barrier for public insurance enrollment (Bansak and Raphael, 2007) and policy changes to reduce them can improve take-up (Fox et al., 2020). For example, Ericson et al. (2023) experimentally implemented a "check the box" streamlined enrollment intervention in Massachusetts' insurance marketplace and found it increased enrollment by 11% with effects concentrated among those eligible for zero-premium plans. Research suggests behavioral factors like complexity, procrastination, and salience of future benefits can also be important Baicker et al. (2012) and small nudge interventions (e.g., information pamphlets, automated phone call reminders) can help (Wright et al., 2017).

Of particular interest to policy-makers, especially during the ACA Medicaid expansions, is the "woodwork" or "welcome-mat" effect (Sonier et al., 2013). The "woodwork effect" refers to the phenomenon where individuals who were already eligible for Medicaid, but had not previously enrolled, come "out of the woodwork" to register when Medicaid expands or undergoes significant policy changes. This surge in enrollment from previously eligible but unenrolled individuals can occur for various reasons, such as increased awareness and publicity about the program, reduced stigma associated with assistance, or enhanced outreach efforts from the state. Push-back by states against the proposed expansions of Medicaid centered around state budget concerns (Murray, 2009; Stanton, 2009). Fear of this woodwork effect further added to concerns over increased costs if a state were to expand Medicaid under the ACA, since only coverage for the newly eligible adults would be financed by the federal government.

Researchers have found evidence of the "welcome-mat" effect following the ACA Medicaid expansions (Frean et al., 2017; Hamersma et al., 2019; Hudson and Moriya, 2017; Sacarny et al., 2022). However, most of the evidence measures the effects of expansions on the previously eligible within the expanding state, and therefore evidence is lacking attempting to disentangle the causes of this effect—to what extent was the "welcome-mat" effect driven by the social channels of interest in the present study (e.g., information, stigma) versus coming from other contemporaneous policy changes that could have made enrollment easier? Understanding the sources of effect are important for future policy design. Moreover, most evidence on the "welcome-mat" effect regards previously eligible children enrolling after their parents become newly eligible. It is not clear that this within-household effect would generalize to a similar effect through adult peers, and it could be driven by non-social factors as the household's total administrative burden also decreases.

3 Empirical Strategy

Given the large increases in Medicaid enrollment caused by the ACA eligibility expansions, I estimate the spillover impacts this might have had on non-expansion states. In other words, I test whether the Medicaid expansions caused a woodwork effect in the non-expansion states through their social connectedness to the expansions.

3.1 Facebook Social Connectedness Index

To proxy for social connections across space I use the Facebook Social Connectedness Index (SCI), created by Bailey et al. (2018a) based on anonymized Facebook user data. The SCI estimates the relative probability of friendships between county-to-county and ZIP code-to-ZIP code pairs. For geographies (e.g., counties) i and j, SCI_{ij} is calculated as the number of Facebook friendship links between users in i and j, divided by the product of i's and j's total Facebook user population

$$SCI_{ij} = \frac{FacebookFriends_{ij}}{FacebookUsers_i \cdot FacebookUsers_j},$$

representing the probability that two representative users in i and j are friends with each other. For privacy reasons, Facebook introduces a scaling factor such that SCI ranges from 1 to 1,000,000,000. SCI is a measure of the relative probability of friendship; if county SCI_{ij} is twice as large, then a representative user in county i is twice as likely to be friends with a representative user in county j.

I use the SCI to proxy for two places' social connectedness, online and offline, not just through Facebook interactions alone. The SCI has been found to correlate strongly with other proxies of connectedness, such as county-to-county migration patterns and trade (Bailey et al., 2018a), and to be an influence in economic behavior (Kuchler and Stroebel, 2021). For example, Hu (2022) find distant environmental shocks impact households' insurance decisions when they are more socially connected to the shocked area. Bailey et al. (2018b) and Bailey et al. (2019) find changes in geographically distant housing markets impact people's house price expectations and purchasing decisions. And Wilson (2022) observes changes in Americans' Earned Income Tax Credit filing behavior when their out-of-state friends experience state EITC implementations.

3.2 Estimating Social Exposure Effects

For each community (e.g., county) p, I define the social exposure to Medicaid expansions as the total number of friends in communities q in states that had expanded Medicaid as of year t, scaled by the communities population (i.e., friends per person):

$$SocialExposure_{p,t} = \sum_{q} pop_q \cdot SCI_{p,q} \cdot MedicaidExpanded_{s(q),t}, \tag{1}$$

where $MedicaidExpanded_{s(q),t} = 1$ if state $s(q)$ had expanded Medicaid as of t and 0 otherwise, and pop_q is q's population, set to 0 if q is in the same state as p. This measure changes over time as more states expand Medicaid and out-of-state communities are more or less exposed to the given states' expansion depending on their degree of social connectedness. I standardize $SocialExposure$ as the z-score so that effects can be interpreted as the impact of having a 1 standard deviation stronger social connectedness to states that have expanded Medicaid.

I estimate the effect of social exposure on outcomes Y for individual i in community p and year t as

$$Y_{ipt} = \alpha + \beta SocialExposure_{p,t} + X'_{ipt}\Gamma + \mu_p + \lambda_{s(p),t} + \varepsilon_{ipt}. \tag{2}$$

The coefficient of interest, β, is the effect of a 1 standard deviation increase in the number of friends (scaled by the number of community residents) who experienced a state Medicaid expansion. X includes state specific controls for income. μ_p are PUMA fixed effects, which absorb any unobserved time invariant characteristics that might be related to Y. $\lambda_{s(p),t}$ are state-by-year fixed effects, which make the comparison between communities within the same state and year and absorb any state-level shocks that might occur over time, such as state policy changes or economic conditions. Therefore, identification comes from within state differences in the community-level social exposure to Medicaid expansions over time; the comparison is between communities in non-expansion states with strong social ties to the expansion states versus communities in the same non-expansion state but with weaker ties to the expansion states, before versus after the expansions. The identifying assumption is that, in the absence of the state expansions, Medicaid enrollment in communities within the same non-expansion state would have evolved similar to each other despite their differing social connections to expansion states.

My treatment of interest in this case, $SocialExposure$, is a continuous measure. Recent research has highlighted the potential challenges and biases TWFE estimators with continuous measures can create (Callaway et al., 2021). To address these issues, I convert $SocialExposure$ to a binary treatment. Specifically, I calculate the within-state median value of $SocialExposure$ in 2018 and consider a PUMA as treated if it surpasses this median value. Some states expanded Medicaid after 2014 and thus treatment is staggered over time. Recent advances in the DiD and event studies literature have called attention to the potential estimation biases that can result from such TWFE designs with staggered adoption (Goodman-Bacon, 2021; **?**; Sun and Abraham, 2021; de de Chaisemartin and D'Haultfœuille, 2020; Roth et al., 2023). In this setting the TWFE regression includes so called "forbidden comparisons" between already-treated units, in addition to desired comparisons between treated and not-yet-treated units. In the presence of treatment effect heterogeneity these comparisons can lead to miss-estimated treatment effect coefficients. Moreover, there could be heterogeneity in how the treatment evolves over time. I address these limitations by estimating dynamic treatment effects using the doubly-robust augmented inverse-probability weighting estimation procedures proposed in Callaway and Sant'Anna (2021). Their methodology decomposes the average treatment effect into a weighted average of group-time-specific treatment effects, which can then be aggregated to the average treatment effects on the treated (ATET) of interests.

3.2.1 Aggregating Social Connectedness

The Facebook SCI is defined for county-to-county and ZIP code-to-ZIP code links. In some analyses, particularly those using American Community Survey data, I use a different geographic unit of analysis. In these cases, I aggregate ZIP code-to-ZIP code SCI to the relevant geographies. Bailey et al. (2021) note that the SCI between two larger regions i and j can be constructed by aggregating the SCI between their sub-regions. Formally, let $r_i \in R(i)$ denote the sub-regions of the larger region i (in my case, ZIP-codes within a PUMA). Let $Friends_{r_i,r_j}$ count the number of friendship links between the sub-regions r_i and r_j, let Pop_{r_i} count the total population in sub-region r_i, and let $PopShare_{r_i}$ denote sub-region r_i's share of the total population in the parent region i. Then SCI_{ij} is equal to a population weighted average of the SCI_{r_i,r_j} between its sub-regions:

$$
\begin{aligned}
SCI_{i,j} = \frac{Friends_{i,j}}{Pop_i \cdot Pop_j} &= \frac{\sum_{r_i \in R(i)} \sum_{r_j \in R(j)} Friends_{r_i,r_j}}{\left(\sum_{r_i \in R(i)} Pop_{r_i}\right) \cdot \left(\sum_{r_j \in R(j)} Pop_{r_j}\right)} \\
&= \sum_{r_i \in R(i)} \sum_{r_j \in R(j)} \frac{Pop_{r_i}}{\sum_{r_i \in R(i)} Pop_{r_i}} \frac{Pop_{r_j}}{\sum_{r_j \in R(j)} Pop_{r_j}} \frac{Friends_{r_i,r_j}}{Pop_{r_i} \cdot Pop_{r_j}} \\
&= \sum_{r_i \in R(i)} \sum_{r_j \in R(j)} PopShare_{r_i} \cdot PopShare_{r_j} \cdot SCI_{r_i,r_j}.
\end{aligned} \tag{3}
$$

I aggregate ZIP code-to-ZIP code SCI to PUMA-to-PUMA SCI under this framework.

3.2.2 Sub-Population Social Connectedness

To explore possible mechanisms I construct alternative versions of PUMA-to-PUMA SCI for specific sub-populations. Note that equation (3) implies that, if I consider subpopulations of an area to be equivalent to sub-regions, the SCI between two areas is made up of a population weighted average of the underlying SCIs between the sub-populations. Consider a partition of the population into two groups, $g \in \{B, W\}$ and two ZIP codes, v and z, with an aggregate social connectedness between them $SCI_{v,z}$. Then, following equation (3), $SCI_{v,z}$ is a weighted average of products of the B and W population shares within each ZIP code and the between- and within-group connectedness between the ZIP codes:

$$
SCI_{v,z} = \sum_{g_v \in \{B_v, W_v\}} \sum_{g_z \in \{B_z, W_z\}} PopShare_{g_v} \cdot PopShare_{g_z} \cdot SCI_{g_v,g_z}.
$$

Here, SCI_{B_v,B_z}, for example, is the within group B connectedness between the B subpopulations in ZIP codes v and z,

$$
SCI_{B_v,B_z} = \frac{Friends_{B_v,B_z}}{Pop_{B_v} \cdot Pop_{B_z}},
$$

and SCI_{B_v,W_z} is the between group B-W connectedness between the B subpopulation in v and the W subpopulation in z.

I assume that within ZIP code pairs, the aggregate SCI between the ZIP codes is equivalent to the subpopulation group SCIs between the ZIP codes (SCI_{g_v,g_z} in the example). I do not assume that this is the case for PUMA-to-PUMA SCI. Then, I can calculate the within group subpopulation connectedness between PUMAs as the aggregation of the ZIP code SCIs but weighted using only the subpopulation of interest. I use this manipulation to construct PUMA-to-PUMA SCI measures specific to language and race/ethnicity subgroups.

3.2.3 Alternative Social Connectedness Proxy: Birth State

Another potential threat to my identification strategy is the possibility of correlated contemporaneous shocks; that is, Medicaid-relevant changes occurring in local (sub-state) areas with more social connections to the Medicaid expansions, occurring around the same time as the expansions. To address this possibility, I employ a different social connectedness proxy in an alternative specification that includes PUMA-year fixed effects to absorb any unobserved local-level changes. Instead of using the SCI as a proxy for social connectedness, which is defined at the local area (PUMA) level, I use an individual's state of birth. People born in a different state are more likely to have social connections to that state than other residents in their neighborhood born in other states. Now, the comparison is between people living within the same PUMA but born in expansion or non-expansion states, before and after their birth states expanded. I estimate this relationship as

$$Y_{ipt} = \alpha + \beta BirthStateExpanded_{s(i),t} + X_{it}'\Gamma + \mu_{p,s(i)} + \lambda_{p,t} + \varepsilon_{ipt}. \tag{4}$$

Now the identifying assumption is that individuals currently living within the same PUMA but born in different states would have Medicaid enrollment evolve similarly in the absence of Medicaid expansions in their birth state. Local, time-varying shocks that impact Medicaid enrollment will not violate the identifying assumptions as long as the shocks do not differentially impact people from different birth states living in that PUMA.

4 Data

4.1 American Community Survey

The main data source for Medicaid enrollment and other population characteristics is the Census Bureau's American Community Survey (ACS). I obtain ACS microdata from IPUMS (Ruggles et al., 2023). The ACS provides a range of demographic and socioeconomic information for a large sample of respondents (about 3 million annually) representing the entire United States. Since 2008, the ACS has asked respondents about their health insurance coverage and source, including whether they are covered by Medicaid, which I use to define Medicaid enrollment.

To identify the potentially eligible population I define income as a percent of the poverty line and other eligibility characteristics. I use the Federal Poverty Guidelines (FPG) issued by the Department of Health and Human Services rather than the poverty thresholds provided by the Census Bureau, since FPG is used for administrative purposes including determining Medicaid eligibility. The State Health Access Data Assistance Center constructs variables for calculating FPG for family unit definitions relevant for health insurance coverage, which can differ from the Census Bureau definitions used for calculating poverty statistics, and provide these modified FPG variables in the IPUMS ACS data. The ACS includes questions about "long lasting" functional limitations, which I use to define disabled as reporting limitations in self-care, independent living, basic ambulatory (e.g., walking, climbing stairs), or cognitive functioning, or severe vision or hearing limitations. The ACS does not include information about current pregnancy and so I do not attempt to identify this eligibility group.

The main geographic unit for all analyses using the ACS is the Public Use Microdata Area (PUMA). PUMAs are defined by the Census Bureau to partition the United States into areas of and no fewer than 100,000 and less than 200,000 people each (only the lower bound is strictly enforced). Delineation of PUMAs occurs after each decennial census, and thus their boundaries can change every 10 years. PUMAs are created by the state data centers in partnership with state, local, and tribal organizations. PUMA boundaries are based on aggregations of census tracts and counties, are contained within states, fall within/outside metropolitan and micropolitan area boundaries wherever possible, and are informed by local knowledge. In sparsely populated areas, PUMAs tend to be larger than counties, and in denser areas they tend to be smaller. The PUMAs defined from the 2010 Census are used in the ACS data beginning in 2012, and for this reason most of the present analyses using ACS data start in 2012.

Table 1 shows summary stats for the main analysis sample, comparing communities below and above their state's median level of social exposure, before and after the expansions. The populations are comparable along most dimensions. Higher social exposure PUMAs are more likely to be in metropolitan areas. Medicaid enrollment was initially lower in the above median PUMAs, but between 2012 and 2018 enrollment grew twice as much in the above median exposure PUMA, leaving them with higher enrollment by the end of the period.

4.2 Cooperative Congressional Elections Study

To explore potential mechanisms I utilize survey data on policy preferences from the Cooperative Congressional Elections Study (CCES). The CCES is an annual, nationally representative survey of over 50,000 respondents. The dataset provides information on voter behavior, public opinion, and policy preferences. Since 2012, the CCES has included a question about whether the respondent supports Congress repealing the ACA. Although this questions does not directly ask about Medicaid, the expansions were a major component of the ACA and therefor respondents' support for the ACA is likely to be related to support for Medicaid expansion.

4.3 California Medicaid Enrollment Counts

To explore social spillover effects from Medicaid expansions in a second setting, I use ZIP-code level monthly enrollment counts from California for 2010–2018. These data provide administrative counts of the number of people enrolled in Medicaid each month with an address in the given ZIP code. Compared to the survey data above, the administrative counts are less subject to measurement error due to misreporting and provide. The monthly ZIP code data also provides information at a more granular geographic and time level.

5 Results: The Social Spillover Effects of Medicaid Expansions

The Medicaid expansions caused a substantial increase in Medicaid enrollment in the expansion states among both the newly and previously eligible population. In addition to enrolling newly eligible beneficiaries, the take-up rate among previously eligible people also increased, and the increase was not restricted to the expansion states (Figure 3). This section estimates the extent to which this increases in take-up in the non-expansion states was caused by the Medicaid expansions through the experiences of people's friends.

Table 2 provides results from estimating equation 2 and shows the effect of an increase in the PUMA's number of friends per person exposed to Medicaid expansion on the probability that a low-income person is enrolled in Medicaid. A 1 standard deviation increase in social exposure resulted in a 0.8 percentage point increase in the probability of being covered by Medicaid, a 4% increase from the baseline level.

Table 2 also shows the impacts on other sources of insurance. The increase in the overall insurance rate is similar to or slightly larger than the increase in Medicaid enrollment. I do not find effects for any other insurance source, including Medicare, other public, employer sponsored, or other private insurance. These findings suggest previously eligible but uninsured adults with stronger social connections to the expansions were more likely to come out of the woodwork and become enrolled, gaining insurance coverage rather than changing insurance sources.

As discussed in Section 3, TWFE regressions may be subject to biases in contexts with staggered treatment adoption timing or continuous treatment variables. Figure 5 shows results from the event study design (dynamic aggregation of ATETs), where the treatment is converted to a binary measure indicating the PUMA has social exposure to Medicaid expansions above the state median. There do not appear to be differential pre-trends, and there is a sharp and sustained increase of 1–2 percentage points after the PUMA reaches above median social exposure.

5.1 An Alternative Social Exposure Proxy

An alternative explanation for the results so far could be that places with stronger connections to the expansion states also experienced other shocks around the same time that affected Medicaid enrollment. For example, it could be that local jurisdictions with closer ties to expansion states share policy views and are more likely to implement enrollment campaigns, which could occur at the same time as the expansions. In this case, I could miss-attribute the effects of local level Medicaid policy efforts to the impact of individuals' social ties.

The results in Table 3 address this possibility by comparing people within the same PUMA and year but with different social exposure to out-of-state expansions, proxied by their birth state. Now, the comparison is between two people subject to the same local level circumstances but with different individual levels of exposure. Using this strategy, I find those with stronger connections to the Medicaid expansions again had a 0.5 percentage point higher probability of becoming Medicaid enrolled. The magnitude of effects is very similar that found using the SCI to proxy for social connections, although the two exposure variables

(SCI and birth state) do not have directly comparable interpretations. These results add confidence that the spillover findings are not being driven by correlated contemporaneous local level shocks.

5.2 A Second Medicaid Expansion Setting

It could also be the case that the spillover effects described so far are specific to the unique context of the ACA Medicaid expansions, which occurred along with other changes to the healthcare system. To test whether the effects generalize to other times, I turn to the California early Medicaid expansions. After the ACA was passed in 2010, a few states decided to expand their Medicaid edibility early in anticipation of the 2014 change. In California, this was implemented as a county roll-out. Some counties, such as the large Los Angeles county, expanded eligibility thresholds in 2011; nearly all counties had expanded by the end of 2012.

Using the same strategy as above, I compare California ZIP codes within the same county but with differential exposure to the expanding counties. I use the ZIP code-to-ZIP code Facebook SCI and monthly ZIP code level administrative enrollment counts to estimate an event study around the first set of expanding counties in 2011, comparing between neighborhoods with above vs below median social exposure.

Figure 6 shows the event study results for the impact on the log of enrollment counts. There do not appear to be differential pre-trends in the 12 months prior to the county expansions. For ZIP codes with above median exposure to the expanding counties, there is an immediate increase that grows over the following months to about a 1.5% increase the number enrolled, with some evidence of the effect dissipating some about a year later. These results provide evidence that the social spillover impacts from expanding eligibility generalize to settings besides the unique context of the 2014 ACA expansion.

5.3 Heterogeneity and Mechanisms

I next turn to examine who is most impacted by these social spillovers. Past literature on network effects in public benefits claiming has relied on geography interacted with personal characteristics, such as race and ethnicity, to proxy for one's social network. I take a similar approach and ask whether social exposure effects are stronger when restricted to within one's own group. For example, someone with Spanish as their main spoken language might live in a neighborhood with lots of friends exposed to the expansion in aggregate but few of whom are Spanish speakers and likely friends with the individual. Conversely, someone might live in an area with low average exposure, but high connectedness to communities within the specific group. As discussed in Section 3.2.2, I create subpopulation specific social exposure variables for those who identify as Hispanic, Black, or report speaking Spanish as their main language at home.

Table 4 shows members within a given subgroup are more effected by their group's social exposure to the Medicaid expansions and do not impact non-members of the group, controlling for the overall aggregate social exposure. For example, consider Spanish speakers in column (1). They were less likely to enrolled in general, but having a 1 standard deviation higher social exposure to the expansions still increased their participation by 1pp. In addition, those in areas with 1 standard deviation higher social exposure to specifically other Spanish speakers in the expansion states saw an additional 1.1pp increase. Similar results are found for the other groups.

5.4 Impacts on Policy Preferences

To further shed light on potential mechanisms driving the effect I turn to the Cooperative Congressional Elections Study (CCES) to study the impact on policy preferences. I test whether social exposure to Medicaid expansions impacts answers to a question about whether the respondent supports Congress repealing the ACA. Although not directly a question about Medicaid, expansion was one of the major and most prominent components of the legislation, and so overall support for the ACA is likely to be related to and affected by support for the Medicaid expansions.

Table 5 shows that counties with more social connection to the Medicaid expansions exhibited more support for the ACA after the expansions. In a second specification I substitute in ZIP code-level SCI instead of county and include county-year fixed effects to compare people within the same county but in ZIP codes with different degrees of social connection to Medicaid expansions; the effect remains strong with social connections proxied at the ZIP code level.

Table 7 shows heterogeneity analyses. I find the effects on policy preferences are concentrated among higher income individuals rather than those who would most likely benefit from the policy change. These results could indicate a role for social exposure to the expansions increasing support for Medicaid in the non-expansion states, which could indirectly lead to improved local administration of the program.

6 Conclusion

The results highlight the intricate dynamics of geographically dispersed social networks and their influence on local public benefits participation. This study contributes to understanding the modern interplay between social ties and economic behavior. Particularly in our rapidly evolving digital age, where social connections are not bound by physical proximity, recognizing the influence of these expansive networks is important. The findings presented here not only highlight the impacts such networks can have on Medicaid enrollment but also shed light on the broader implications for various public programs. For policymakers, public program designs and implementations should take into account the potential influence of distant social connections. Policy changes in one jurisdiction can resonate beyond its immediate confines, creating effects that may not be immediately obvious but are profound in their implications. Considering these unforeseen spillovers and indirect influences is important for anticipating program outcomes, and understanding of the interconnected fabric of our social and economic landscape.

References

Aizer, Anna, "Low Take-Up in Medicaid: Does Outreach Matter and for Whom?," *American Economic Review*, May 2003, *93* (2), 238–241.

_ , "Public Health Insurance, Program Take-Up, and Child Health," *The Review of Economics and Statistics*, August 2007, *89* (3), 400–415.

_ **and Janet Currie**, "Networks or Neighborhoods? Correlations in the Use of Publicly-Funded Maternity Care in California," *Journal of Public Economics*, December 2004, *88* (12), 2573–2585.

Anders, Jenna and Charlie Rafkin, "The Welfare Effects of Eligibility Expansions: Theory and Evidence from SNAP," 2022.

Baicker, Katherine, William J. Congdon, and Sendhil Mullainathan, "Health Insurance Coverage and Take-Up: Lessons from Behavioral Economics," *The Milbank Quarterly*, 2012, *90* (1), 107–134.

Bailey, Michael, Abhinav Gupta, Sebastian Hillenbrand, Theresa Kuchler, Robert Richmond, and Johannes Stroebel, "International Trade and Social Connectedness," *Journal of International Economics*, March 2021, *129*, 103418.

_ **, Eduardo Dávila, Theresa Kuchler, and Johannes Stroebel**, "House Price Beliefs And Mortgage Leverage Choice," *The Review of Economic Studies*, November 2019, *86* (6), 2403–2452.

_ **, Rachel Cao, Theresa Kuchler, Johannes Stroebel, and Arlene Wong**, "Social Connectedness: Measurement, Determinants, and Effects," *Journal of Economic Perspectives*, June 2018, *32* (3), 259–80.

_ **, Ruiqing Cao, Theresa Kuchler, and Johannes Stroebel**, "The Economic Effects of Social Networks: Evidence from the Housing Market," *Journal of Political Economy*, December 2018, *126* (6), 2224–2276.

Bansak, Cynthia and Steven Raphael, "The Effects of State Policy Design Features on Take-up and Crowd-out Rates for the State Children's Health Insurance Program," *Journal of Policy Analysis and Management*, 2007, *26* (1), 149–175.

Bertrand, Marianne, Erzo F P Luttmer, and Sendhil Mullainathan, "Network Effects and Wlefare Cultures," *Quarterly Journal of Economics*, 2000, *115* (3).

Bhargava, Saurabh and Dayanand Manoli, "Psychological Frictions and the Incomplete Take-Up of Social Benefits: Evidence from an IRS Field Experiment," *American Economic Review*, November 2015, *105* (11), 3489–3529.

Brantley, Erin and Sara Rosenbaum, "Ballot Initiatives Have Brought Medicaid Eligibility To Many But Cannot Solve The Coverage Gap," 2021.

Callaway, Brantly and Pedro H.C. Sant'Anna, "Difference-in-Differences with Multiple Time Periods," *Journal of Econometrics*, 2021, *225* (2), 200–230.

_ , Andrew Goodman-Bacon, and Pedro H. C. Sant'Anna, "Difference-in-Differences with a Continuous Treatment," July 2021.

Chetty, Raj, John N. Friedman, and Emmanuel Saez, "Using Differences in Knowledge across Neighborhoods to Uncover the Impacts of the EITC on Earnings," *American Economic Review*, December 2013, *103* (7), 2683–2721.

Courtemanche, Charles, James Marton, Benjamin Ukert, Aaron Yelowitz, and Daniela Zapata, "Early Impacts of the Affordable Care Act on Health Insurance Coverage in Medicaid Expansion and Non-Expansion States," *Journal of Policy Analysis and Management*, 2017, *36* (1), 178–210.

Currie, Janet and Valentina Duque, "Medicaid: What Does It Do, and Can We Do It Better?," *Annals of the American Academy of Political and Social Science*, 2019, *686* (1), 148–179.

_ , Sandra Decker, and Wanchuan Lin, "Has Public Health Insurance for Older Children Reduced Disparities in Access to Care and Health Outcomes?," *Journal of Health Economics*, December 2008, *27* (6), 1567–1581.

Dahl, Gordon B., Andreas Ravndal Kostøl, and Magne Mogstad, "Family Welfare Cultures," *The Quarterly Journal of Economics*, November 2014, *129* (4), 1711–1752.

_ , Katrine V. Løken, and Magne Mogstad, "Peer Effects in Program Participation," *American Economic Review*, July 2014, *104* (7), 2049–2074.

de de Chaisemartin, Clément and Xavier D'Haultfœuille, "Two-Way Fixed Effects Estimators with Heterogeneous Treatment Effects," *American Economic Review*, September 2020, *110* (9), 2964–96.

Decker, Sandra L., Salam Abdus, and Brandy J. Lipton, "Eligibility for and Enrollment in Medicaid Among Nonelderly Adults After Implementation of the Affordable Care Act," *Medical care research and review: MCRR*, February 2022, *79* (1), 125–132.

DellaVigna, Stefano and Woojin Kim, "Policy Diffusion and Polarization across U.S. States," June 2022.

Ericson, Keith Marzilli, Timothy J. Layton, Adrianna McIntyre, and Adam Sacarny, "Reducing Administrative Barriers Increases Take-up of Subsidized Health Insurance Coverage: Evidence from a Field Experiment," January 2023.

Finkelstein, Amy and Matthew J Notowidigdo, "Take-Up and Targeting: Experimental Evidence from SNAP*," *The Quarterly Journal of Economics*, August 2019, *134* (3), 1505–1556.

Fox, Ashley M., Edmund C. Stazyk, and Wenhui Feng, "Administrative Easing: Rule Reduction and Medicaid Enrollment," *Public Administration Review*, 2020, *80* (1), 104–117.

Frean, Molly, Jonathan Gruber, and Benjamin D. Sommers, "Premium Subsidies, the Mandate, and Medicaid Expansion: Coverage Effects of the Affordable Care Act," *Journal of Health Economics*, May 2017, *53*, 72–86.

Gilens, Martin, *Why Americans Hate Welfare: Race, Media, and the Politics of Antipoverty Policy* Studies in Communication, Media, and Public Opinion, Chicago, IL: University of Chicago Press, October 2000.

Goodman-Bacon, Andrew, "Difference-in-Differences with Variation in Treatment Timing," *Journal of Econometrics*, June 2021.

Gray, Virginia, "Innovation in the States: A Diffusion Study," *American Political Science Review*, 1973, *67* (4), 1174–1185.

Grossman, Daniel and Umair Khalil, "Neighborhood Networks and Program Participation," *Journal of Health Economics*, March 2020, *70*, 102257.

Hamersma, Sarah, Matthew Kim, and Brenden Timpe, "The Effect of Parental Medicaid Expansions on Children's Health Insurance Coverage," *Contemporary Economic Policy*, 2019, *37* (2), 297–311.

Heckman, J.J. and J.A. Smith, "The Determinants of Participation in a Social Program: Evidence from a Prototypical Job Training Program," *Journal of Labor Economics*, 2004, *22* (2), 243–298.

Hu, Zhongchen, "Social Interactions and Households' Flood Insurance Decisions," *Journal of Financial Economics*, May 2022, *144* (2), 414–432.

Hudson, Julie L. and Asako S. Moriya, "Medicaid Expansion For Adults Had Measurable 'Welcome Mat' Effects On Their Children," *Health Affairs (Project Hope)*, September 2017, *36* (9), 1643–1651.

Janssens, Julie and Natascha Van Mechelen, "To Take or Not to Take? An Overview of the Factors Contributing to the Non-Take-up of Public Provisions," *European Journal of Social Security*, June 2022, *24* (2), 95–116.

Jensen, Carsten and Michael Bang Petersen, "The Deservingness Heuristic and the Politics of Health Care," *American Journal of Political Science*, 2017, *61* (1), 68–83.

Kaiser Family Foundation, "Medicaid's Role in Nursing Home Care," 2017.

_ , "Status of State Medicaid Expansion Decisions," https://www.kff.org/medicaid/issue-brief/status-of-state-medicaid-expansion-decisions-interactive-map/ 2023.

Keiser, Lael R. and Susan M. Miller, "Does Administrative Burden Influence Public Support for Government Programs? Evidence from a Survey Experiment," *Public Administration Review*, 2020, *80* (1), 137–150.

Kenney, Genevieve M, Jennifer M Haley, Clare Pan, Victoria Lynch, and Matthew Buettgens, "Medicaid/CHIP Participation Rates Rose among Children and Parents in 2015," Technical Report, Urban Institute 2015.

Kenney, Genevieve M., Victoria Lynch, Jennifer Haley, and Michael Huntress, "Variation in Medicaid Eligibility and Participation among Adults: Implications for the Affordable Care Act," *INQUIRY: The Journal of Health Care Organization, Provision, and Financing*, August 2012, *49* (3), 231–253.

Ko, Wonsik and Robert A. Moffitt, "Take-up of Social Benefits," June 2022.

Kuchler, Theresa and Johannes Stroebel, "Social Finance," *Annual Review of Financial Economics*, November 2021, *13* (1), 37–55.

Linos, Katerina, *The Democratic Foundations of Policy Diffusion: How Health, Family, and Employment Laws Spread Across Countries*, Oxford, New York: Oxford University Press, April 2013.

Miller, Sarah and Laura R. Wherry, "Four Years Later: Insurance Coverage and Access to Care Continue to Diverge between ACA Medicaid Expansion and Non-Expansion States," *AEA Papers and Proceedings*, May 2019, *109*, 327–333.

Moffitt, Robert, "An Economic Model of Welfare Stigma," *American Economic Review*, 1983, *73* (5), 1023–1035.

Murray, Shailagh, "States Resist Medicaid Growth; Governors Fear For Their Budgets," *The Washington Post*, October 2009, p. A.1.

Nicholson-Crotty, Jill, Susan M. Miller, and Lael R. Keiser, "Administrative Burden, Social Construction, and Public Support for Government Programs," *Journal of Behavioral Public Administration*, March 2021, *4* (1).

Roth, Jonathan, Pedro H. C. Sant'Anna, Alyssa Bilinski, and John Poe, "What's Trending in Difference-in-Differences? A Synthesis of the Recent Econometrics Literature," *Journal of Econometrics*, April 2023.

Ruggles, Steven, Matthew Sobek, Danika Brockman, Grace Cooper, Stephanie Richards, and Megan Schouweiler, "IPUMS USA: Version 13.0 [Dataset]," 2023.

Sacarny, Adam, Katherine Baicker, and Amy Finkelstein, "Out of the Woodwork: Enrollment Spillovers in the Oregon Health Insurance Experiment," *American Economic Journal: Economic Policy*, August 2022, *14* (3), 273–295.

Shigeoka, Hitoshi and Yasutora Watanabe, "Policy Diffusion Through Elections," July 2023.

Shipan, Charles R. and Craig Volden, "The Mechanisms of Policy Diffusion," *American Journal of Political Science*, 2008, *52* (4), 840–857.

Sommers, Benjamin D., Meredith Roberts Tomasi, Katherine Swartz, and Arnold M. Epstein, "Reasons For The Wide Variation In Medicaid Participation Rates Among States Hold Lessons For Coverage Expansion In 2014," *Health Affairs*, May 2012, *31* (5), 909–919.

Sonier, Julie, Michel H. Boudreaux, and Lynn A. Blewett, "Medicaid 'welcome-Mat' Effect of Affordable Care Act Implementation Could Be Substantial," *Health Affairs (Project Hope)*, July 2013, *32* (7), 1319–1325.

Stanton, John, "GOP Senators, Governors Fear Health Care Burden on States," https://www.rollcall.com/2009/09/17/gop-senators-governors-fear-health-care-burden-on-states/ September 2009.

Stuber, Jennifer and Mark Schlesinger, "Sources of Stigma for Means-Tested Government Programs," *Social Science & Medicine*, August 2006, *63* (4), 933–945.

Stuber, Jennifer P, Kathleen A Maloy, Sara Rosenbaum, and Karen C Jones, "Beyond Stigma: What Barriers Actually Affect the Decisions of Low-Income Families to Enroll in Medicaid?," Technical Report 2000.

Sun, Liyang and Sarah Abraham, "Estimating Dynamic Treatment Effects in Event Studies with Heterogeneous Treatment Effects," *Journal of Econometrics*, December 2021, *225* (2), 175–199.

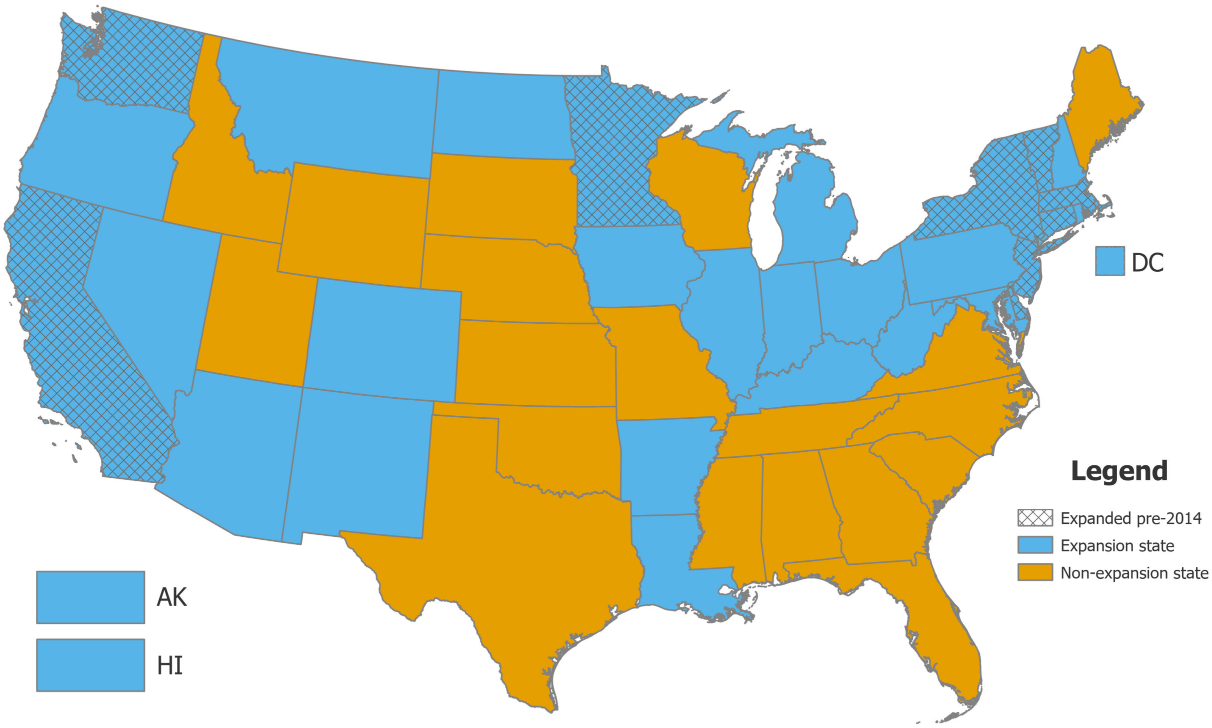
Walker, Jack L., "The Diffusion of Innovations among the American States," *American Political Science Review*, 1969, *63* (3), 880–899.

Wilson, Riley, "The Impact of Social Networks on EITC Claiming Behavior," *The Review of Economics and Statistics*, September 2022, *104* (5), 929–945.

Wright, Bill J., Ginny Garcia-Alexander, Margarette A. Weller, and Katherine Baicker, "Low-Cost Behavioral Nudges Increase Medicaid Take-Up Among Eligible Residents Of Oregon," *Health Affairs*, May 2017, *36* (5), 838–845.

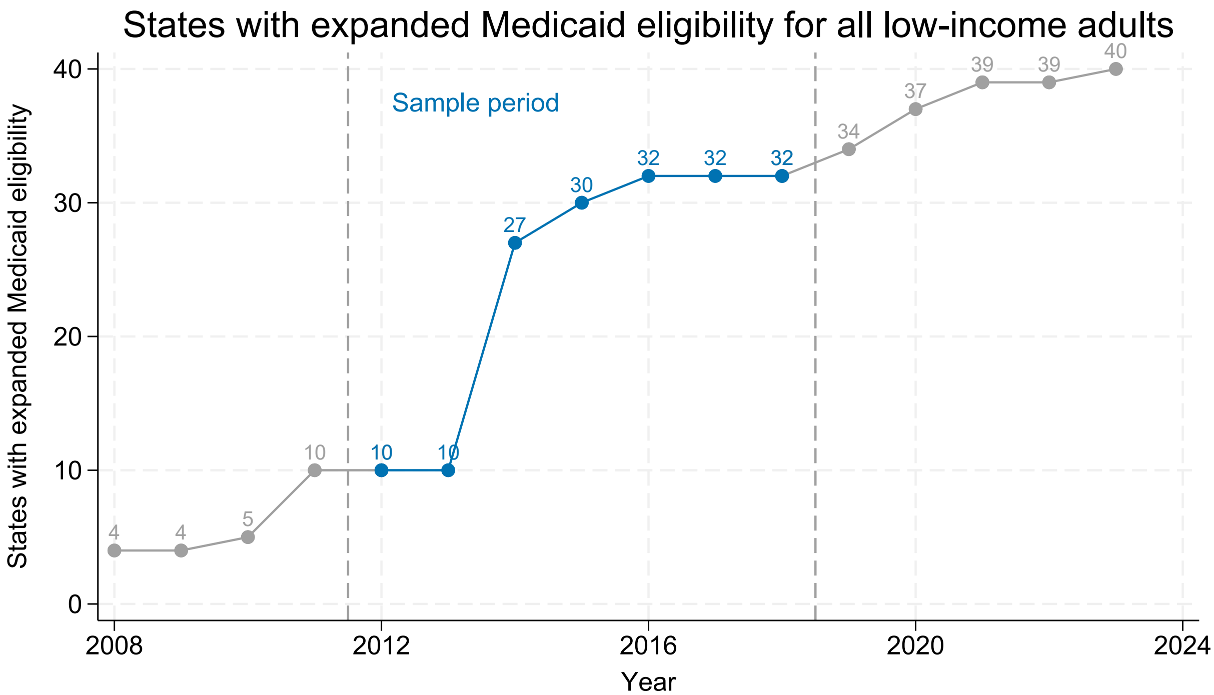
7 Figures

Figure 1: States' ACA Medicaid expansion status in 2018



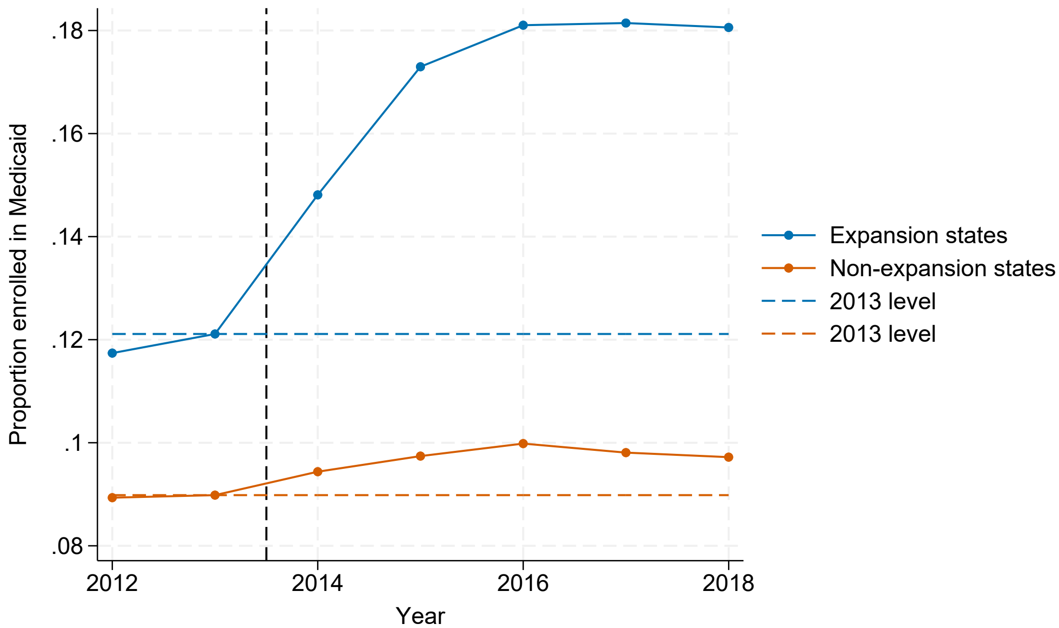
Notes: This map shows states' Medicaid expansion status—extending eligibility to all low-income (<138% poverty) adults—as of 2018. States with Medicaid programs that covered all low-income adults before the 2014 ACA expansions are defined as already expanded. Data come from the Kaiser Family Foundation (Kaiser Family Foundation, 2023) and are supplemented with additional state information. Four states already had Medicaid programs that covered all low-income adults before passage of the ACA: Delaware since 1996, Massachusetts since 2006, New York since 2001, and Vermont since 2000. Four states (Connecticut, California, Minnesota, New Jersey) and the District of Columbia expanded Medicaid early between passage of the ACA in 2010 and the ACA Medicaid expansions beginning 2014. Connecticut and New Jersey adopted expansions early in 2011 for adults under 56% and 23% of the poverty line, respectively, and are included as early expanders. California expanded early with staggered adoption across counties during 2011–2014 and is included as an early expander. Eight states expanded Medicaid between 2019 and 2023, seven of which were through ballot initiatives. North Carolina adopted expansion in March, 2023, but has not yet implemented the expansion.

Figure 2: State ACA Medicaid expansions trend

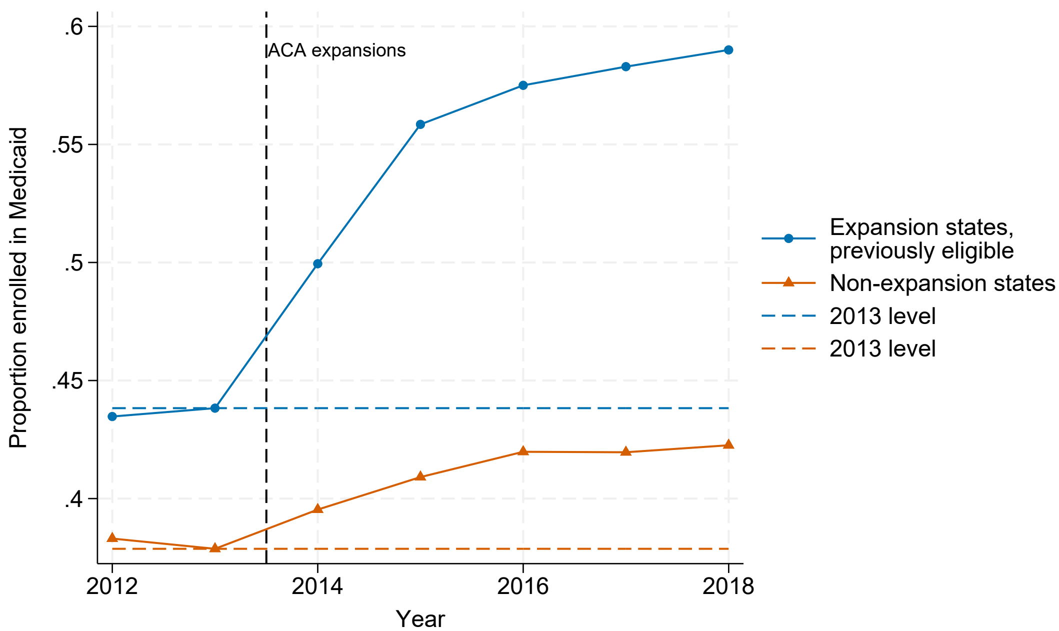


Notes: This figure shows the trend in the number of states that had expanded Medicaid to cover all low-income (<138% poverty) adults. States with Medicaid programs that covered all low-income adults before the ACA expansions are defined as expanded; early expanding states are described in the notes to Figure 1. Dashed lines delineate the beginning and end of the study period.

Figure 3: Trends in Medicaid enrollment and take-up in 2012–2018



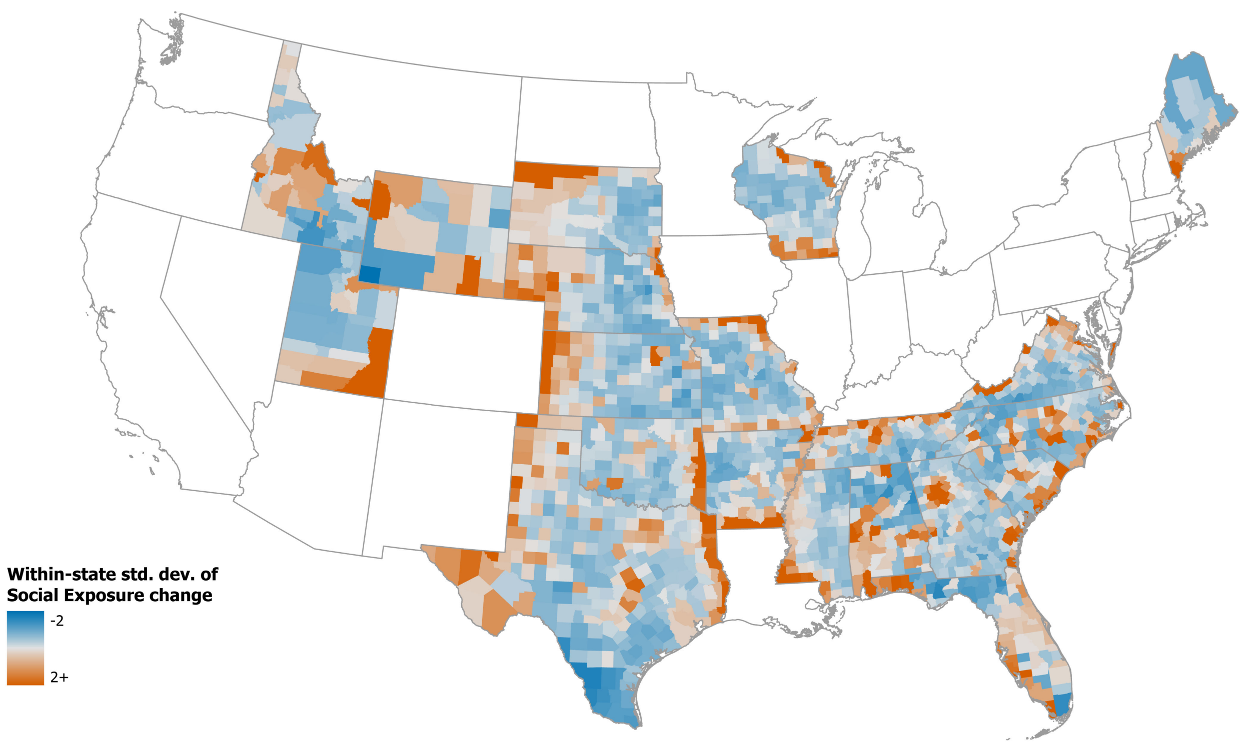
(a) Enrollment among non-elderly adult population



(b) Take-up among eligible non-elderly adults

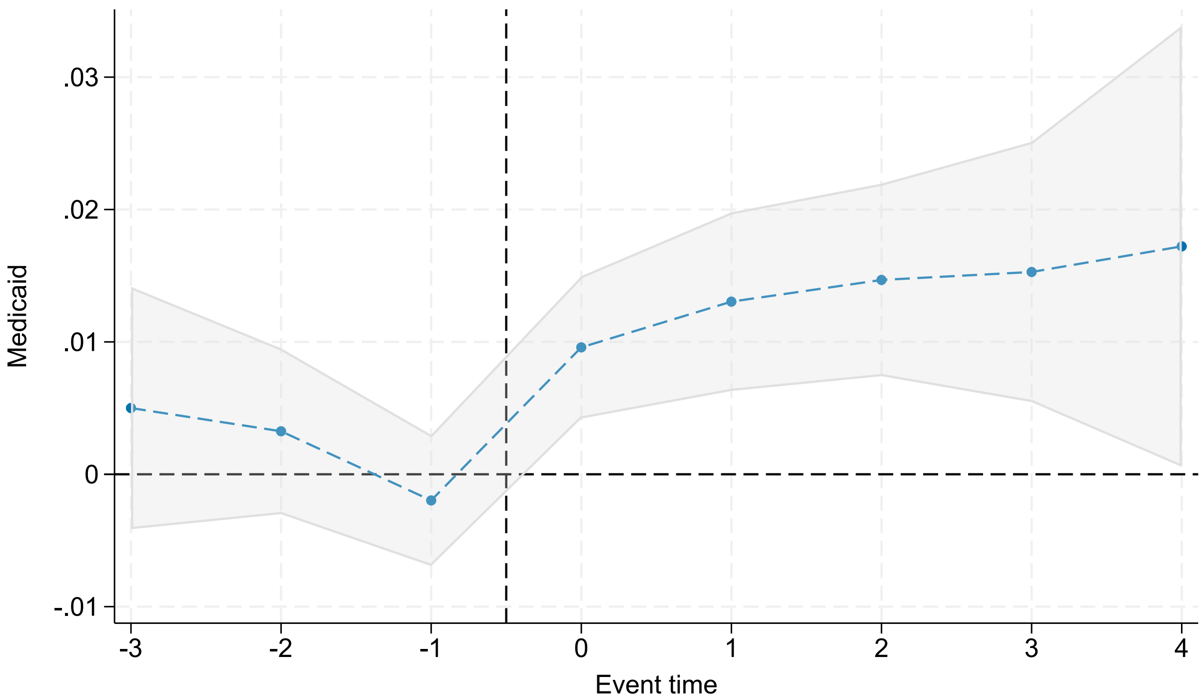
Notes: Panel (a) shows trends in the proportion of the overall non-elderly adult (26–64) population enrolled in Medicaid in expansion and non-expansion states. Dashed lines show the proportion enrolled in 2013 for reference. Panel (b) shows trends in the proportion of the eligible non-elderly adult population enrolled. For expansion states, trends are shown for those eligible under 2013 rules.

Figure 4: County-level social exposure to Medicaid expansions



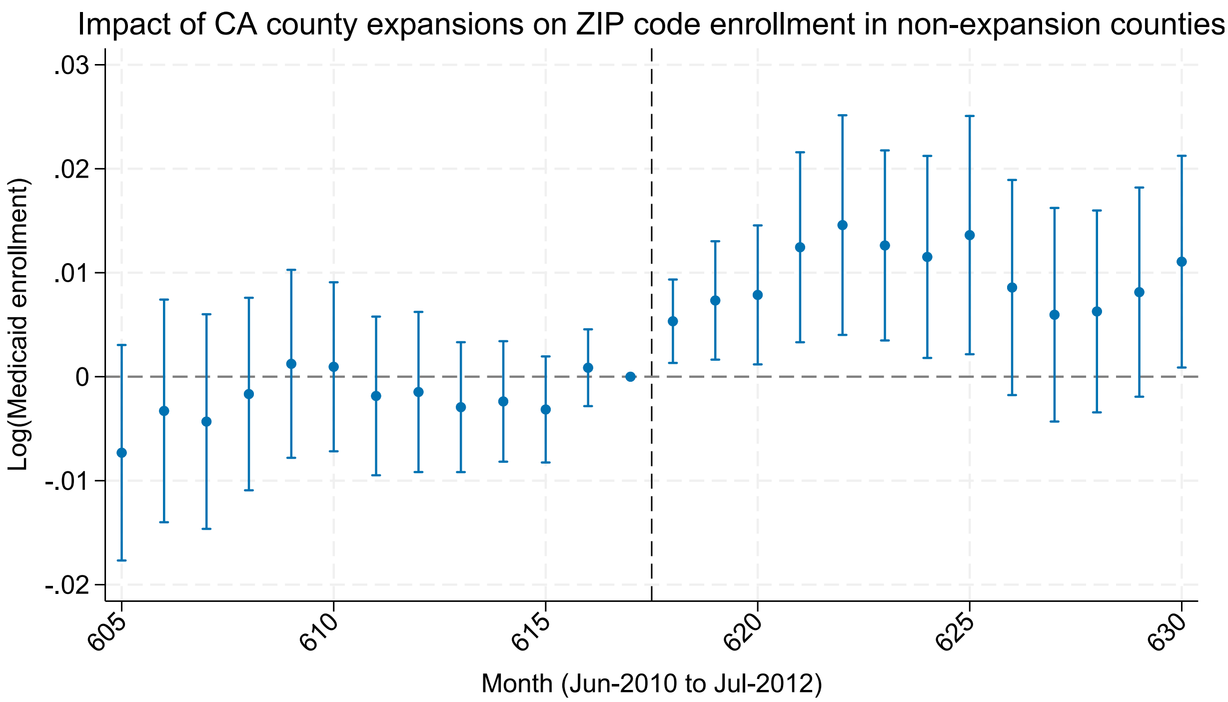
Notes: This map shows county-level social exposure to 2014–2016 Medicaid expansions in non-expansion states. Social exposure standardized within state as z-score.

Figure 5: Event study for impact of above-median social exposure to Medicaid expansions on enrollment, potentially eligible adults ages 26–64 in non-expansion states, 2012–2018



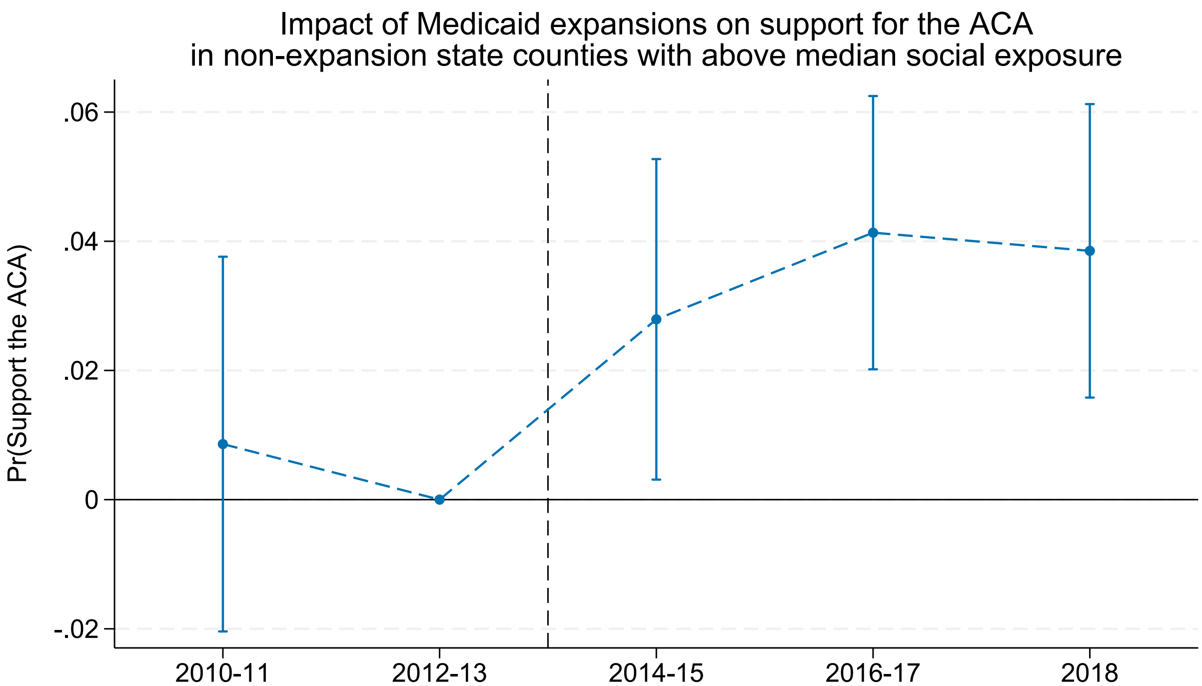
Notes: This figure shows the dynamic average treatment effects on the treated for the impact of social exposure to Medicaid expansions on the probability of enrollment using the augmented inverse-probability weighting estimation procedures in (Callaway and Sant'Anna, 2021). Controls in both the outcome and selection equations include respondent age, sex, race/ethnicity, education, parental status, employment status, and whether they migrated into the state in the past year. Regressions weighted using ACS person-level analysis weights.

Figure 6: Event study for impact of above-median social exposure to California county Medicaid expansions on ZIP code-level enrollment



Notes:

Figure 7: Impact of above median social exposure to Medicaid expansions on county-level approval of the ACA



Notes:

8 Tables

Table 1: Summary statistics for main analysis sample, low-income adults ages 26–64 in non-expansion states

	Mean population characteristics in:			
	2012-13		2017-18	
	Social exposure:		Social exposure:	
	Below median	Above median	Below median	Above median
Male	0.48	0.47	0.47	0.46
Age (years)	43.0	42.4	43.2	42.7
Race/ethnicity				
NH-white	0.50	0.48	0.48	0.46
NH-Black	0.19	0.27	0.19	0.27
Hispanic	0.26	0.19	0.28	0.20
NH-other	0.04	0.06	0.05	0.07
Parent status (ages 18+)				
Non parent	0.51	0.53	0.53	0.54
Single parent	0.21	0.22	0.22	0.22
Married parent	0.27	0.25	0.25	0.23
Educational attainment				
Less than high school	0.24	0.19	0.21	0.17
High school	0.45	0.42	0.46	0.43
Some coll	0.22	0.25	0.22	0.24
BA+	0.09	0.14	0.10	0.16
Employment (ages 18-64)				
employed	0.48	0.50	0.50	0.52
unemployed	0.10	0.11	0.06	0.07
not in labor force	0.42	0.39	0.44	0.41
Disabled	0.22	0.20	0.22	0.21
Metropolitan area	0.60	0.84	0.61	0.84
Income (% of FPG)	92.1	94.4	93.7	95.7
Any health insurance	0.55	0.57	0.65	0.68
Medicaid	0.22	0.20	0.24	0.24

Notes: Social Exposure is based on the Facebook Social Connectedness Index (Bailey et al., 2018a) and measures the number of friendship links between the given PUMA and all PUMAs in states that have expanded Medicaid, scaled by the PUMA 2020 population; above- and below-median defined within state. Low-income includes those with health insurance unit (HIU) income <200% of the Federal Poverty Guidelines (FPG). Statistics weighted by ACS person-level analysis weights.

Table 2: Effect of social network exposure to Medicaid expansions on health insurance coverage by source, low-income Americans ages 26–64 in non-expansion states, 2012–2018

	Probability of reporting health insurance coverage from:					
	Medicaid (1)	Medicare (2)	Other public (3)	Employer (4)	Other private (5)	Any insurance (6)
Social Exposure	0.008***	0.001	0.000	0.004	0.000	0.009**
	(0.002)	(0.002)	(0.001)	(0.003)	(0.003)	(0.004)
PUMA fixed effects	Y	Y	Y	Y	Y	Y
State-year fixed effects	Y	Y	Y	Y	Y	Y
Income controls	Y	Y	Y	Y	Y	Y
R-squared	0.055	0.014	0.050	0.110	0.028	0.076
Outcome mean, 2012-13	0.211	0.092	0.043	0.247	0.089	0.557
Number of PUMAs	911	911	911	911	911	911
Number of observations	1,402,206	1,402,206	1,402,206	1,402,206	1,402,206	1,402,206

Notes: *** $p < .01$, ** $p < .05$, * $p < .10$. Standard errors (in parentheses) clustered at the PUMA level. Social Exposure is based on the Facebook Social Connectedness Index (Bailey et al., 2018a) and measures the number of friendship links between the given PUMA and all PUMAs in states that have expanded Medicaid, scaled by the PUMA 2020 population. Low-income includes those with health insurance unit (HIU) income <200% of the Federal Poverty Guidelines (FPG). Income controls indicates inclusion of state-specific linear controls for the ratio of HIU income/FPG. Regressions weighted using ACS person-level analysis weights.

Table 3: Effect of exposure to Medicaid expansions using birthplace as proxies for social connection, potentially eligible Americans ages 26-64 in non-expansion states, 2012-2018

	Probability enrolled in Medicaid		
	(1)	(2)	(3)
Birth-state's Medicaid expanded	0.005**	0.005*	0.005*
	(0.003)	(0.003)	(0.003)
Income controls	Y	Y	Y
PUMA-treat group fixed effects	Y	Y	Y
PUMA-year fixed effects	Y	Y	Y
Exclude foreign-born		Y	
Exclude in-state-born			Y
R-squared	0.081	0.067	0.094
Outcome mean, 2012-13	0.211	0.240	0.173
Number of PUMAs	911	911	911
Number of observations	1,402,158	1,141,939	683,279

Notes: *** $p < .01$, ** $p < .05$, * $p < .10$. Standard errors (in parentheses) clustered at the PUMA level. Potentially eligible defined as below the poverty line and a parent or disabled. Individual controls include age, sex, race/ethnicity, education, parental status, employment status, and whether they migrated into the state in the past year. The six treatment groups are: born in state, born out of the country, born out of state in a non-expansion state, born out of state in an expansion state that expanded in 2014, 2015, and 2016. Regressions weighted using ACS person-level analysis weights.

Table 4: Effects of subgroup-specific social network exposure on Medicaid enrollment, potentially eligible Americans ages 26-64 in non-expansion states, 2012-2018

	Probability enrolled in Medicaid For subgroup:		
	Spanish speaker	Hispanic	Black, non-Hisp.
Subgroup member # Subgroup social exposure	0.011***	0.013***	0.007***
	(0.003)	(0.002)	(0.002)
Subgroup social exposure	−0.004	−0.008**	−0.004
	(0.004)	(0.004)	(0.003)
Subgroup member	−0.092***	−0.088***	0.071***
	(0.003)	(0.003)	(0.003)
Overall social exposure	0.010***	0.012***	0.008**
	(0.003)	(0.003)	(0.004)
Income controls	Y	Y	Y
PUMA fixed effects	Y	Y	Y
State-year fixed effects	Y	Y	Y
R-squared	0.060	0.060	0.059
Number of PUMAs	911	911	911
Number of observations	1,402,206	1,402,206	1,402,206

Notes: *** $p < .01$, ** $p < .05$, * $p < .10$. Standard errors (in parentheses) clustered at the PUMA level. Subgroup social exposure is an alternative definition of social exposure which is restricted to the within subgroup members of an individual's network; overall social exposure is the baseline measure. Potentially eligible defined as below the poverty line and a parent, disabled, or elderly, or below 200% and a child. Individual controls include age, sex, race/ethnicity, education, parental status, employment status, and whether they migrated into the state in the past year. Regressions weighted using ACS person-level analysis weights.

Table 5: Effect of social exposure to Medicaid expansions on support for the Affordable Care Act, American adults in non-expansion states, 2012-2018

	Pr(Support the ACA)		
	(1)	(2)	(3)
Social Exposure (county)	0.022**	0.003	
	(0.009)	(0.012)	
Social Exposure (ZIP code)		0.019***	0.020***
		(0.005)	(0.005)
Individual controls	Y	Y	Y
County fixed effects	Y	Y	
State-year fixed effects	Y	Y	
County-year fixed effects			Y
Outcome mean	0.454	0.454	0.454
R-squared	0.269	0.268	0.314
Number of counties	1,500	1,392	1,358
Number of observations	136,983	134,397	132,408

Notes: *** $p < .01$, ** $p < .05$, * $p < .10$. Standard errors (in parentheses) clustered at the county level. Individual controls include age, sex, race and ethnicity, education, marital status, parental status, household income, health insurance status, and political party. Column (2) drops observations missing ZIP codes or ZIP code level exposure, and column (3) drops observations due to insufficient observations in some counties.

Table 6: Effect of social exposure to Medicaid expansions on preferences for state policy, American adults in non-expansion states, 2012-2018

	Respondent supports their state:		
	Expand Medicaid	Increase healthcare spend	Increase welfare spend
	(1)	(2)	(3)
Soc Exp change (ZIP)	0.046***	0.022**	0.012
	(0.017)	(0.010)	(0.007)
County-year FEs	Y	Y	Y
Individual controls	Y	Y	Y
N	20,027	67,132	67,132
r2	0.248	0.200	0.171

Notes: *** $p < .01$, ** $p < .05$, * $p < .10$. Standard errors (in parentheses) clustered at the county level. Individual controls include age, sex, race and ethnicity, education, marital status, parental status, household income, health insurance status, and political party.

Table 7: Effect of social exposure to Medicaid expansions on support for the Affordable Care Act, American adults in non-expansion states, 2012-2018

	Pr(Support the ACA)	
	(1)	(2)
Social Exposure (county)	−0.014	0.024***
	(0.011)	(0.009)
Income # Social Exposure (county)		
20k-50k	0.027***	
	(0.007)	
50k-80k	0.033***	
	(0.008)	
80k-120k	0.051***	
	(0.008)	
120k+	0.062***	
	(0.008)	
Prefer not to say	0.043***	
	(0.009)	
Income		
20k-50k	−0.003	0.001
	(0.007)	(0.010)
50k-80k	−0.009	−0.005
	(0.008)	(0.011)
80k-120k	−0.015*	−0.003
	(0.008)	(0.011)
120k+	−0.013	0.006
	(0.009)	(0.012)
Prefer not to say	−0.040***	−0.031***
	(0.008)	(0.011)
Would benefit from expansion # Social Exposure (county)		
1		−0.022***
		(0.008)
Would benefit from expansion		
1		0.001
		(0.013)
Individual controls	Y	Y
County fixed effects	Y	Y
State-year fixed effects	Y	Y
Outcome mean	0.454	0.454
R-squared	0.270	0.270
Number of counties	1,500	1,500
Number of observations	136,983	136,983

Notes: *** $p < .01$, ** $p < .05$, * $p < .10$. Standard errors (in parentheses) clustered at the county level. Individual controls include age, sex, race and ethnicity, education, marital

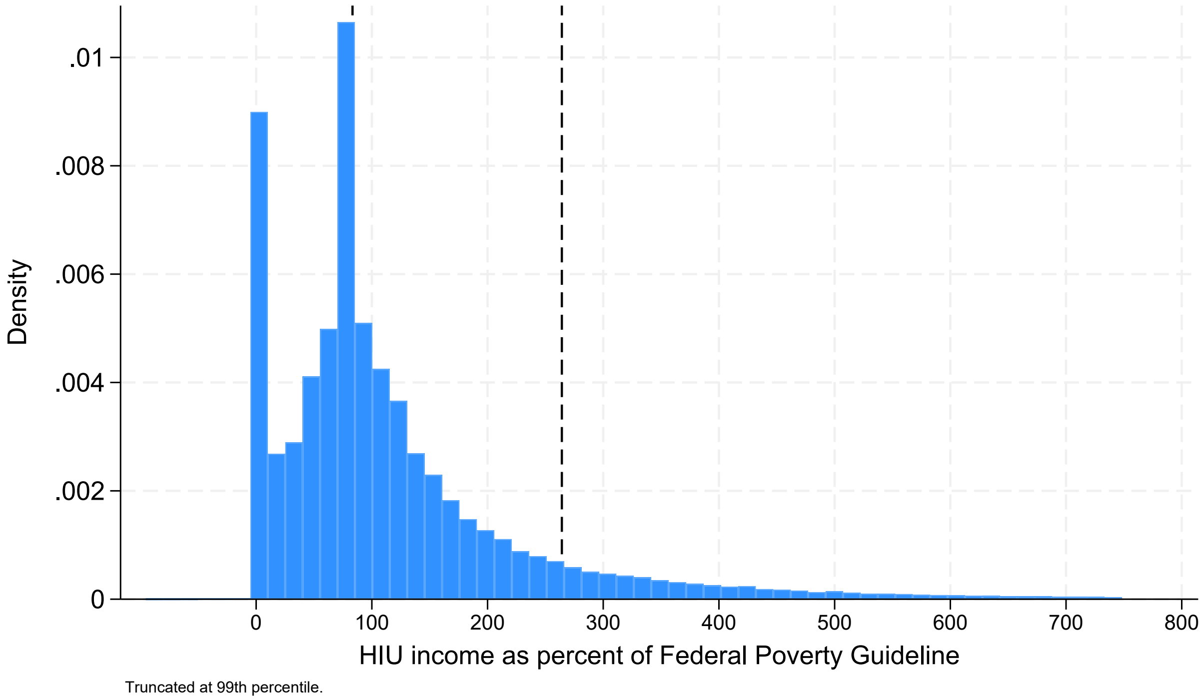
9 Supplemental Exhibits

Table S1: Summary statistics for Medicaid enrolled population

	Non-expansion states		Expansion states	
	2012-13	2017-18	2012-13	2017-18
Male	0.46	0.46	0.46	0.47
Age				
<18	0.54	0.52	0.46	0.38
18-25	0.08	0.07	0.09	0.10
26-39	0.10	0.11	0.13	0.17
40-64	0.16	0.17	0.20	0.24
65+	0.12	0.13	0.12	0.11
Race/ethnicity				
NH-white	0.43	0.42	0.44	0.43
NH-Black	0.27	0.26	0.18	0.16
Hispanic	0.24	0.26	0.28	0.29
NH-other	0.06	0.07	0.10	0.11
Parent status (ages 18+)				
Non parent	0.60	0.62	0.57	0.61
Single parent	0.23	0.22	0.23	0.20
Married parent	0.17	0.16	0.19	0.19
Educational attainment				
Less than high school	0.67	0.63	0.60	0.51
High school	0.21	0.23	0.24	0.28
Some coll	0.08	0.09	0.11	0.14
BA+	0.03	0.04	0.05	0.07
Employment (ages 18-64)				
employed	0.28	0.34	0.34	0.45
unemployed	0.11	0.07	0.13	0.09
not in labor force	0.61	0.59	0.53	0.46
disabled	0.25	0.24	0.24	0.22
HIU income (% of FPG)	118	136	123	144
Eligible for Medicaid (strict)	0.54	0.53	0.61	0.71
Eligible for Medicaid (semi-strict)	0.71	0.68	0.73	0.78

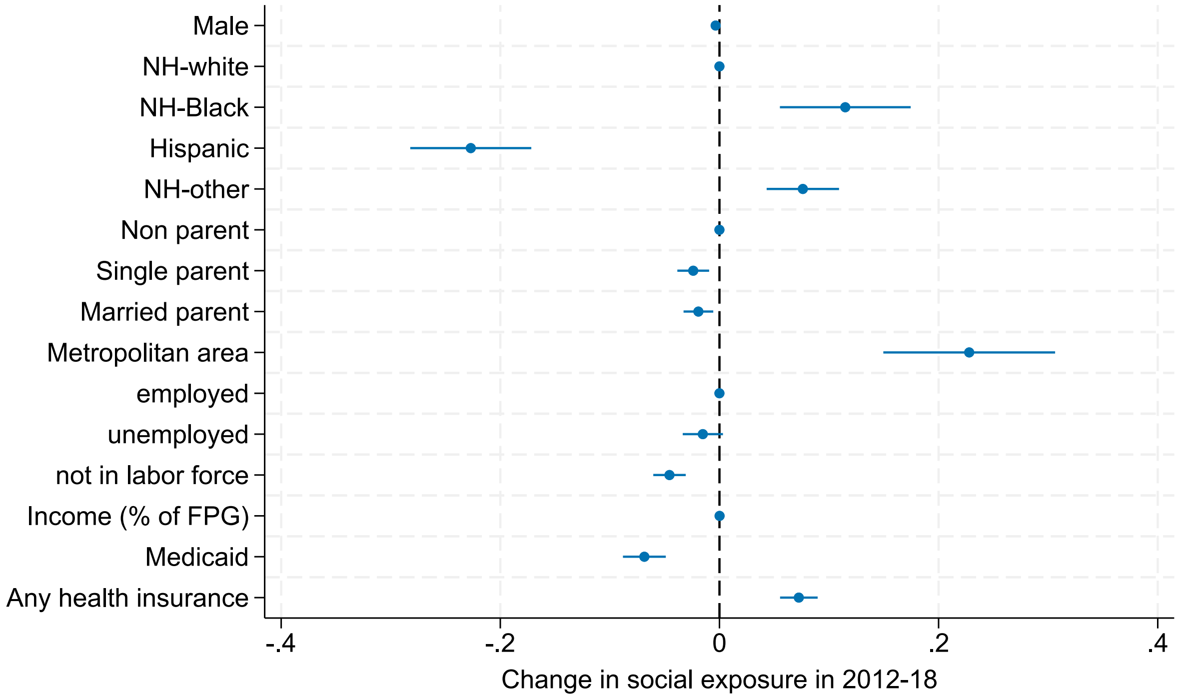
Notes: Statistics weighted by ACS person-level analysis weights.

Figure S1: Income distribution for Medicaid enrolled adults ages 26–64 in non-expansion states, 2012–2018



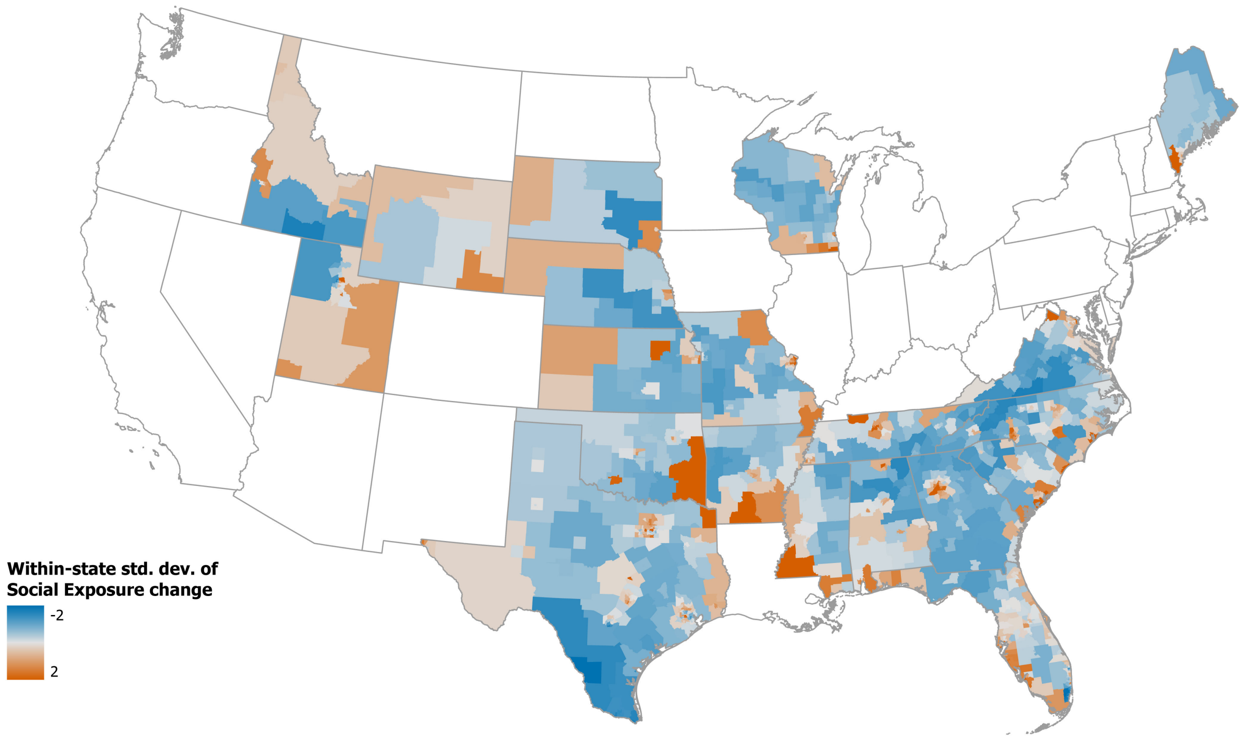
Notes:

Figure S2: PUMA population characteristics associated with Social Exposure



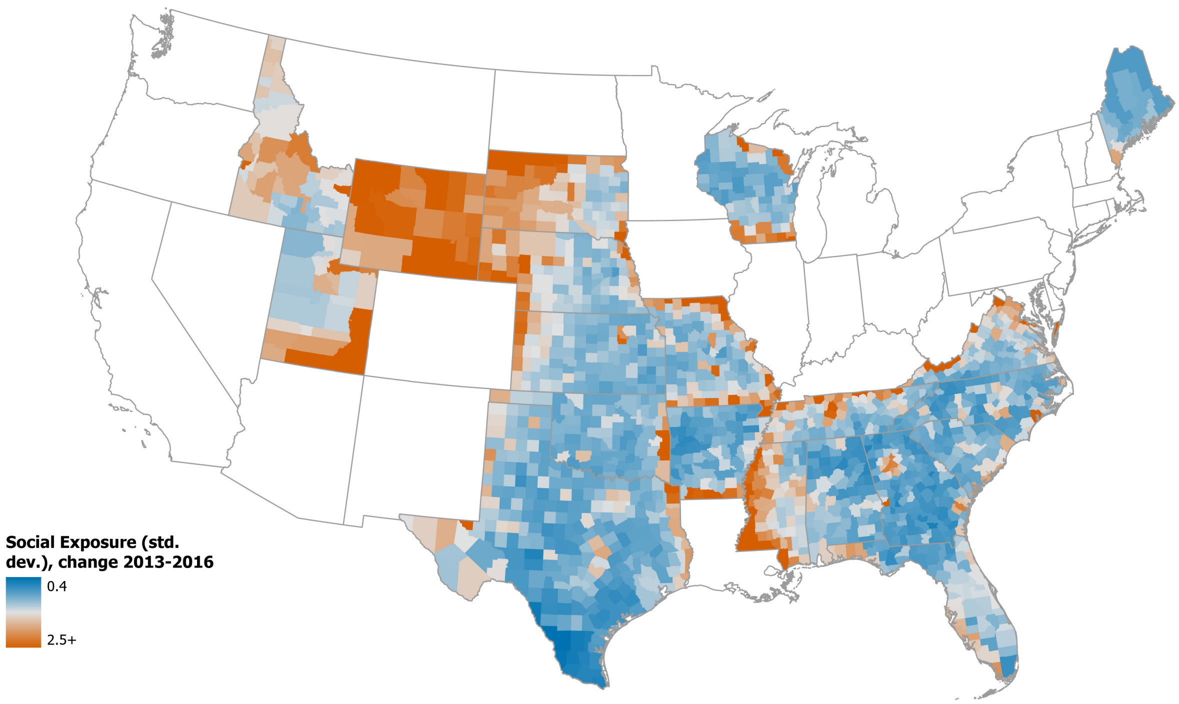
Notes:

Figure S3: PUMA-level social exposure to Medicaid expansions



Notes: This map shows PUMA-level social exposure to 2014–2016 Medicaid expansions in non-expansion states. Social exposure standardized within state as z-score.

Figure S4: County-level social exposure to Medicaid expansions



Notes: This map shows county-level social exposure to 2014–2016 Medicaid expansions in non-expansion states, as standard deviation change in friends per person exposed to Medicaid eligibility expansion.

Table S2: Alternative versions of social network exposure, potentially eligible Americans ages 27-64 in non-expansion states, 2012-2018

	Social exposure measure used:				
	Friends per person	Binary	New elig. friends/person	Percent of network	Network's elig. thresh.
Social Exposure	0.008***	0.006***	0.006***	0.069***	0.052***
	(0.002)	(0.002)	(0.002)	(0.019)	(0.016)
PUMA fixed effects	Y	Y	Y	Y	Y
State-year fixed effects	Y	Y	Y	Y	Y
Income controls	Y	Y	Y	Y	Y
R-squared	0.055	0.055	0.055	0.055	0.055
Outcome mean, 2012-13	0.211	0.211	0.211	0.211	0.211
Number of PUMAs	911	911	911	911	911
Number of observations	1,402,206	1,402,206	1,402,206	1,402,206	1,402,206

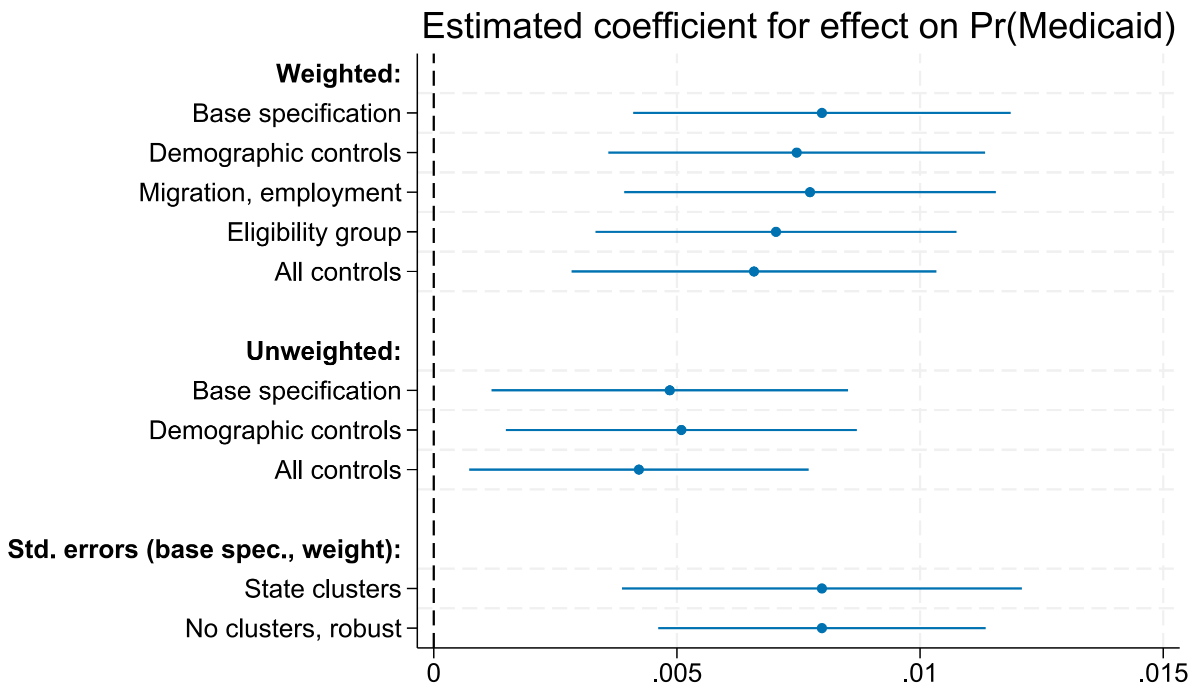
Notes: *** $p < .01$, ** $p < .05$, * $p < .10$. Standard errors (in parentheses) clustered at the PUMA level. Potentially eligible defined as below the poverty line and a parent or disabled. Excluding friends within 100 and 200 miles columns use social exposure measures constructed from social networks with friends within these distances excluded. New beneficiary exposure uses a social exposure measure constructed with exposure defined as the percent change in Medicaid enrollment instead of a binary indicator of Medicaid expansion. The Binary column uses the treatment definition used in Figure 5. Individual controls include age, sex, race/ethnicity, education, parental status, employment status, and whether they migrated into the state in the past year. Regressions weighted using ACS person-level analysis weights.

Table S3: Effect of social network exposure to Medicaid expansions on Medicaid enrollment, by age, low-income Americans in non-expansion states, 2012-2018

				age			
	Ages 0-10	Ages 11-17	Ages 18-25	Ages 26-39	Ages 40-54	Ages 55-64	Ages 65+
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Social Exposure	0.004	0.006	−0.001	0.009***	0.008**	0.003	−0.002
	(0.005)	(0.006)	(0.003)	(0.003)	(0.004)	(0.005)	(0.004)
PUMA fixed effects	Y	Y	Y	Y	Y	Y	Y
State-year fixed effects	Y	Y	Y	Y	Y	Y	Y
Income controls	Y	Y	Y	Y	Y	Y	Y
R-squared	0.126	0.098	0.036	0.072	0.056	0.044	0.077
Outcome mean, 2012-13	0.691	0.577	0.134	0.194	0.213	0.247	0.264
Number of PUMAs	911	911	911	911	911	911	911
Number of observations	521,176	318,318	633,423	569,669	486,338	346,199	633,436

Notes: *** $p < .01$, ** $p < .05$, * $p < .10$. Standard errors (in parentheses) clustered at the PUMA level. Social Exposure is based on the Facebook Social Connectedness Index (Bailey et al., 2018a) and measures the number of friendship links between the given PUMA and all PUMAs in states that have expanded Medicaid, scaled by the PUMA 2020 population. Low-income includes those with health insurance unit (HIU) income <200% of the Federal Poverty Guidelines (FPG). Income controls indicates inclusion of state-specific linear controls for the ratio of HIU income/FPG. Regressions weighted using ACS person-level analysis weights.

Figure S5: Estimated effect of social exposure on Medicaid enrollment using alternative specifications, low-income adults ages 26–64 in 2012–2018



Notes: