# The Social Spillover Effects of Changing Program Eligibility: Evidence from Out-of-State Medicaid Expansions

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**Abstract**

Understanding the influence of individuals' social networks on their interactions with public programs is important for evaluating program outcomes and shaping future policy. In contexts where social frictions, such as incomplete information and stigma, are prevalent, policy changes might cause unanticipated indirect impacts operating through social channels. This paper studies social spillover effects arising from changes in program eligibility criteria and how they impact the previously- and non-eligible populations not targeted by the policy change. I focus on state-level changes to Medicaid, the United States' low-income public health insurance program, during the 2010s. Using the Facebook Social Connectedness Index to capture network connections across ZIP codes, I isolate social spillover effects by estimating the impacts out-of-state eligibility expansions had on interactions with Medicaid in socially connected communities within non-expansion states. Areas with 1 standard deviation stronger social ties to states expanding Medicaid eligibility experienced 1-2pp increases in program take-up following the policy change, 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. I explore the roles of information

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and stigma as potential channels of effect. 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.

# 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 public 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 changes.

I first estimate effects on Medicaid enrollment using American Community Survey data. I find that potentially eligible non-elderly adults in Public Use Microdata Areas (PUMAs) with one standard deviation more friends per person in Medicaid expansion states were 1.3 percentage points more likely to be enrolled in Medicaid after the 2014 ACA expansions—even though eligibility was largely unchanged for themselves—compared to communities in the same state but with less social connections to the expansions. The impact on Medicaid enrollment was reflected in the uninsured rate (1.6 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. The effects translate to an overall Medicaid take-up rate in non-expansion states that was 1.6 percentage point higher in 2018 than it would have otherwise been without the presence of social spillovers from the expansions, resulting in about 110,000 more individuals covered by Medicaid in 2018.

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

[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.

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 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 Inde-*

[3] Although Medicaid and CHIP are separate programs, states may bundle their administration and management and thus they are often considered as parts of the same broad program.

*pendent 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 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 Data

## 3.1 Facebook Social Connectedness Index

As the main proxy of 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 $j$.

Since PUMAs are the main geographic unit of analysis, I aggregate the ZIP code-to-ZIP code SCI to PUMA-to-PUMA SCI. 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 $SCI_{ij}$ can be shown to equal a population weighted average of the $SCI_{r_i,r_j}$ between its sub-regions:

$$\begin{aligned} SCI_{i,j} = \frac{Friends_{i,j}}{Pop_i \cdot Pop_j} &= \frac{\sum_{r_i \in R(i)} \sum_{r_j \in R(j)} Friends_{r_i,r_j}}{\left(\sum_{r_i \in R(i)} Pop_{r_i}\right) \cdot \left(\sum_{r_j \in R(j)} Pop_{r_j}\right)} \\ &= \sum_{r_i \in R(i)} \sum_{r_j \in R(j)} \frac{Pop_{r_i}}{\sum_{r_i \in R(i)} Pop_{r_i}} \frac{Pop_{r_j}}{\sum_{r_j \in R(j)} Pop_{r_j}} \frac{Friends_{r_i,r_j}}{Pop_{r_i} \cdot Pop_{r_j}} \\ &= \sum_{r_i \in R(i)} \sum_{r_j \in R(j)} PopShare_{r_i} \cdot PopShare_{r_j} \cdot SCI_{r_i,r_j}. \end{aligned} \tag{1}$$

I aggregate ZIP code-to-ZIP code SCI to PUMA-to-PUMA SCI under this framework. In some alternative specifications and additional analyses I utilize the county-to-county SCI. The construction of the various versions of SCI used throughout the analyses is described in detail in Appendix **??**.

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 American Community Survey

My 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.

## 3.3 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 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.

## 4.1 Estimating Social Exposure Effects

To proxy for social connectedness I use the Facebook SCI, described in section 3.1. For each PUMA $p$, I construct the social exposure to Medicaid expansions as the weighted average of its social connectedness to out-of-state PUMAs $q$ in states that had expanded Medicaid as of year $t$:

$$SocialExposure_{p,t} = \sum_{q} w_q \cdot SCI_{p,q} \cdot MedicaidExpanded_{s(q),t}, \tag{2}$$

where $MedicaidExpanded_{s(q),t} = 1$ if state $s(q)$ had expanded Medicaid as of $t$ and 0 otherwise, and $w_q$ are population weights with $w_q = 0$ if $q$ is in the same state as $p$. This measure changes over time as more states expand Medicaid and out-of-state PUMAs 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 Medicaid enrollment among already potentially eligible individuals (low income parents and disabled adults ages 27-64) in non-expansion states. Specifically for individual $i$ in PUMA $p$, I estimate the probability of being enrolled in Medicaid in year $t$ in TWFE models as follows

$$Y_{ipt} = \alpha + \beta SocialExposure_{p,t} + X'_{it}\Gamma + \mu_p + \lambda_{s(p),t} + \varepsilon_{ipt}. \tag{3}$$

The coefficient of interest, $\beta$, is the effect of a 1 standard deviation increase in social exposure to Medicaid expansions on $Y$, the probability of being enrolled in Medicaid. $\mu_p$ are PUMA fixed effects, which absorb any unobserved time invariant characteristics that might be related to Medicaid enrollment. $\lambda_{s(p),t}$ are state-by-year fixed effects, which make the comparison between PUMAs within the same state and year and absorb any state level shocks that might occur over time, such as state-level policy changes. Therefore, identification comes from within state differences in the PUMA-level social exposure to Medicaid expansions over time; the comparison is between PUMAs in non-expansion states with strong social ties to the expansion states versus PUMAs 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 PUMAs 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.

#### 4.1.1 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.

### 4.1.2 Sub-Population Social Networks

To explore possible mechanisms I construct alternative versions of PUMA-to-PUMA SCI for specific sub-populations. Note that equation (1) 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 (1), $SCI_{v,z}$ 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 subgroups

# 5 Results: The Social Spillover Effects of Medicaid Expansions

## 5.1 Social Network Exposure Effects in Non-Expansion States

The Medicaid expansions caused a substantial increase in Medicaid enrollment in the expansion states. I next turn to the question of whether these impacts influenced potential beneficiaries' decisions to enroll in Medicaid in non-expansion states through their social networks. Specifically, this section tests the hypothesis that people in non-expansion states who had stronger social connections to expansion states exhibited more of a woodwork effect than those with less social connection.

Table S4 shows results from estimating equation (3) by age group. Similar to the direct impacts of Medicaid expansions, the effects are concentrated among mid-aged adults. I find a 1 standard deviation increase in the extent of social exposure to Medicaid expansions increased Medicaid enrollment by 1.2 percentage points among potentially eligible adults age 27-64. The effect is attenuated when the sample is expanded to include young adults, and I find no statistically significant impacts on children or those over 65. For the remainder of the analyses on enrollment I focus on the age 27-64 population.

Table 1 shows the estimated impact on insurance coverage by source. The increase in the overall insurance rate is similar to or slightly larger than the increase in Medicaid enrollment. I do not find similar 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.

Figure 6 shows results from the event study design, 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 about 1 percentage point after the PUMA reaches above median social exposure.

### 5.1.1 Alternative Strategies and Robustness Checks

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 S2 address this possibility by comparing people within the same local area and year but with different social exposure to out-of-state expansions, proxied by their birth state. Using this strategy I find those with stronger connections to the Medicaid expansions again had a 1–2 percentage point higher probability of becoming Medicaid enrolled. The magnitude of effects if very similar that found using the SCI to proxy for social connections, although the two exposure variables (SCI and birth state) do not have a directly comparable interpretation.

## 5.2 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 2 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 **??** 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.

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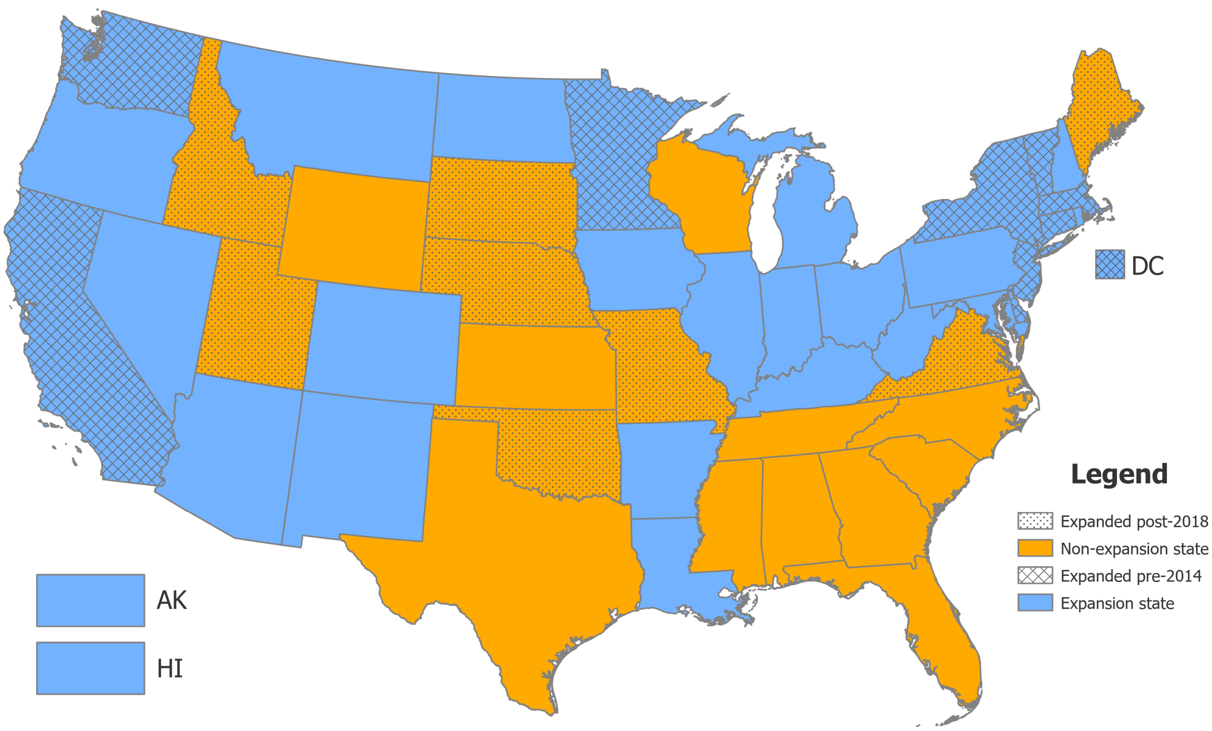
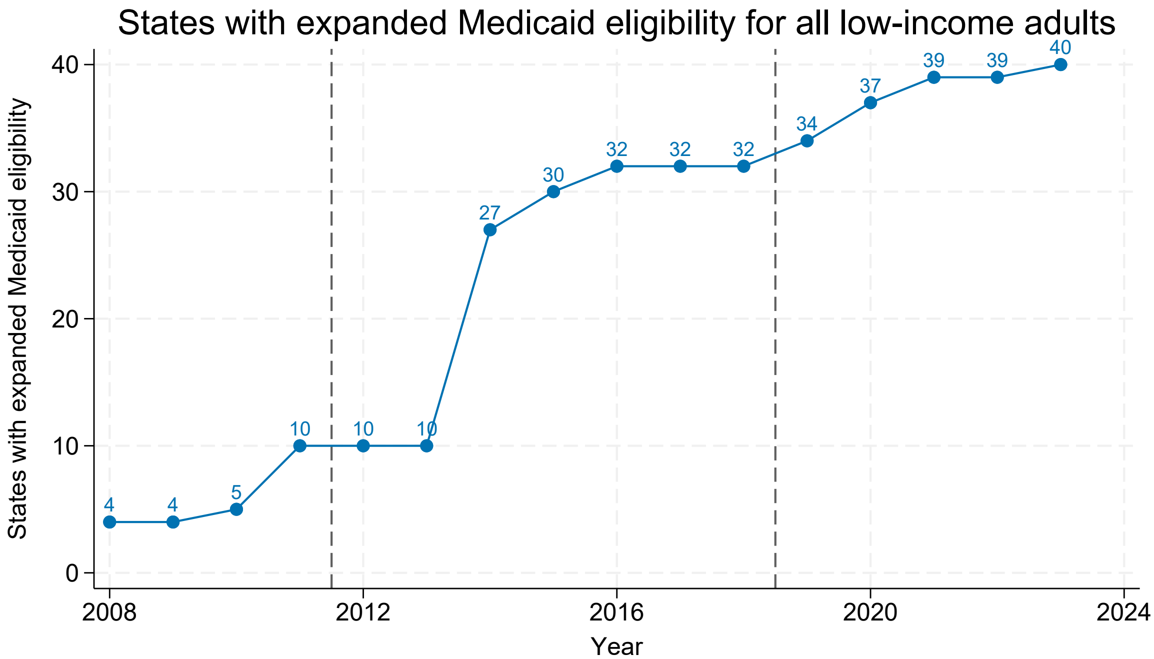
# 7 Figures

Figure 1: States' ACA Medicaid expansion status in 2018



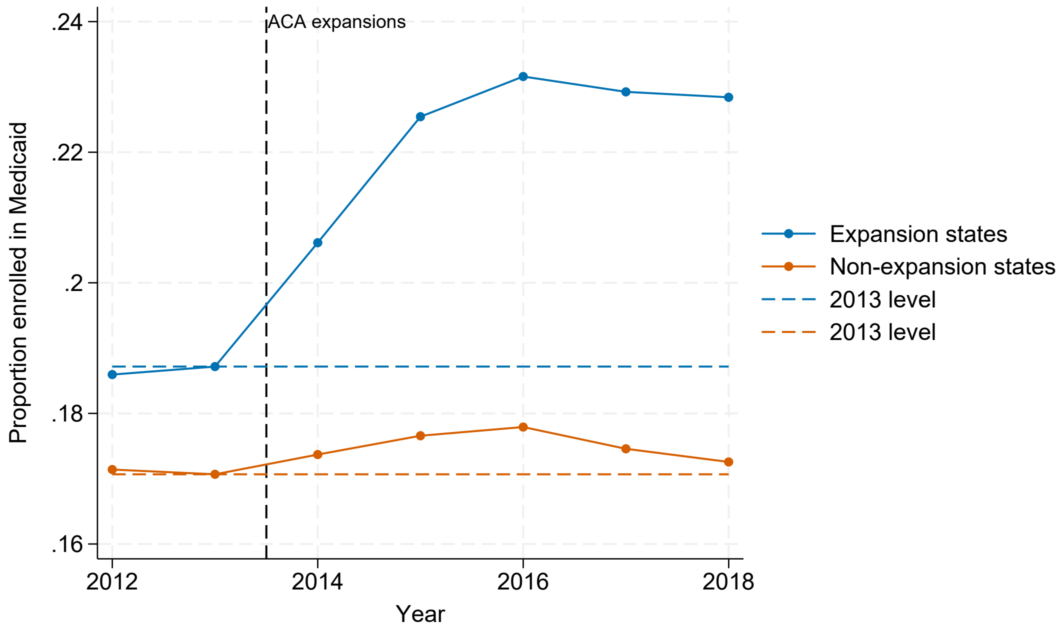

Notes: This map shows states' Medicaid expansion status—extending eligibility to all low-income (<138% poverty) adults—as of 2018. States with Medicaid programs that covered all low-income adults before the 2014 ACA expansions are defined as already expanded. Data come from the Kaiser Family Foundation (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, 2008–2023

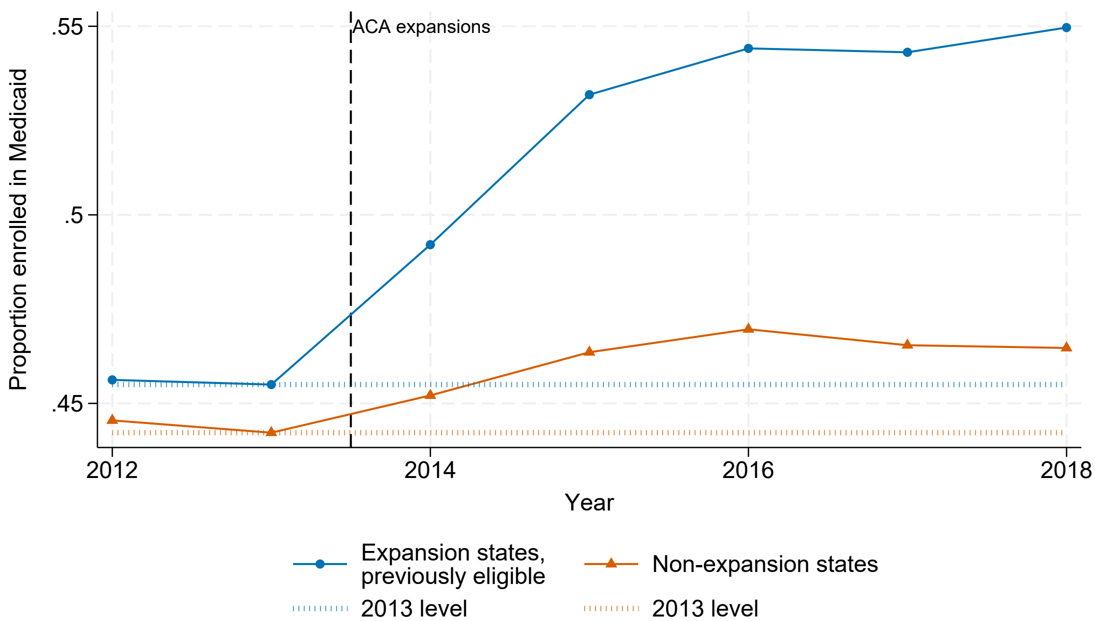



Notes: This figure shows the trend in the number of states that had expanded Medicaid to cover all low-income (<138% poverty) adults. States with Medicaid programs that covered all low-income adults before the ACA expansions are defined as expanded; early expanding states are described in the notes to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



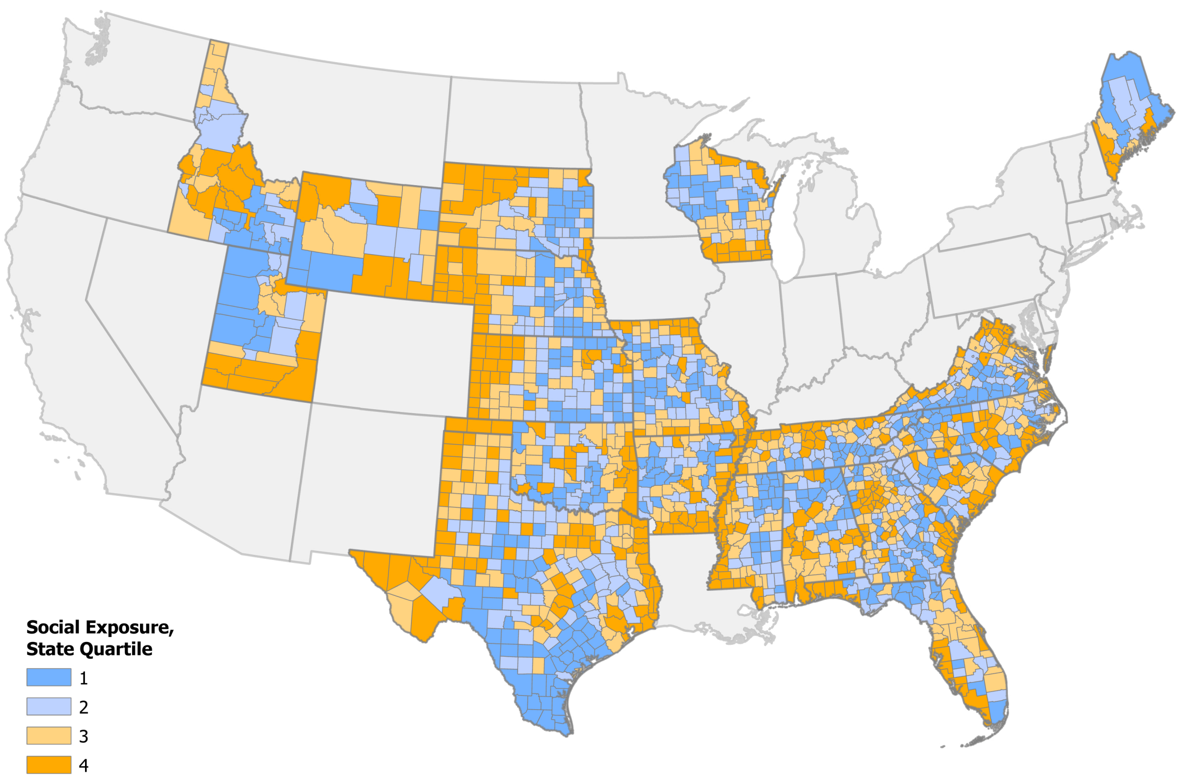

A. Enrollment among the total non-elderly adult population




B. Take-up among eligible non-elderly adults

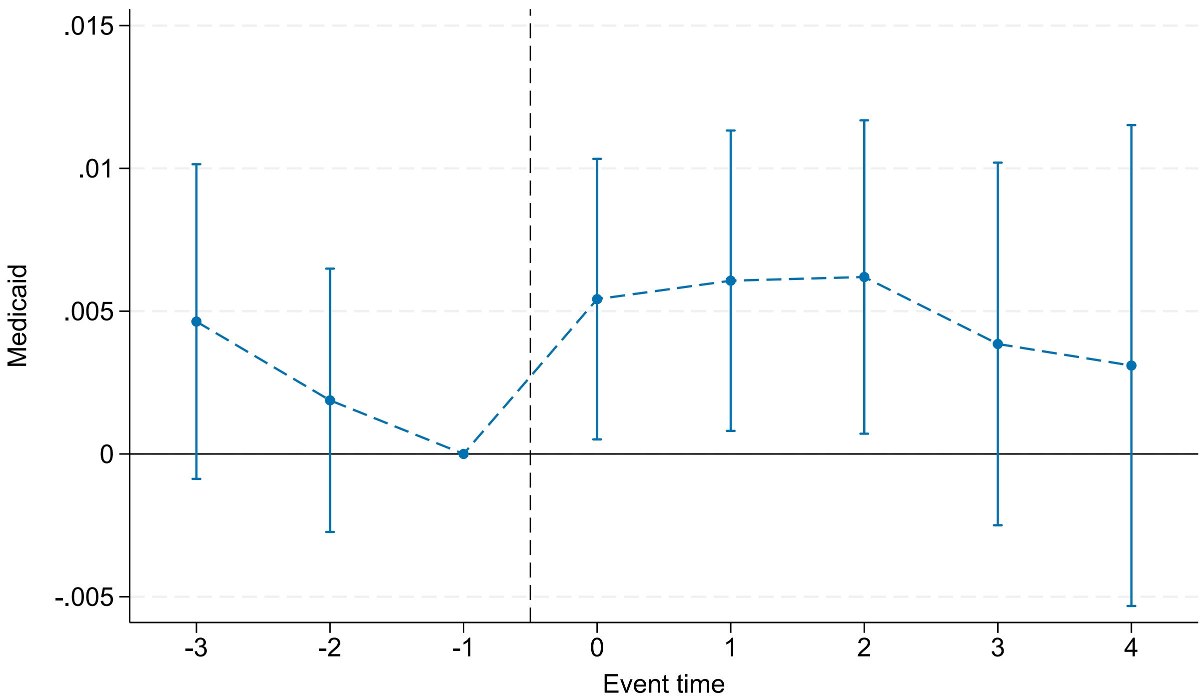
Notes: Panel A shows trends in the proportion of the overall non-elderly adult (18–64) population enrolled in Medicaid in expansion and non-expansion states. Dashed lines show the proportion enrolled in 2013 for reference. Panel B shows trends in the proportion of the eligible non-elderly adult population enrolled. For expansion states, trends are shown for those eligible under 2013 rules as well as for the total eligible population (i.e., including the large increase in eligibles started in 2014).

Figure 4: County-level social exposure to Medicaid expansions



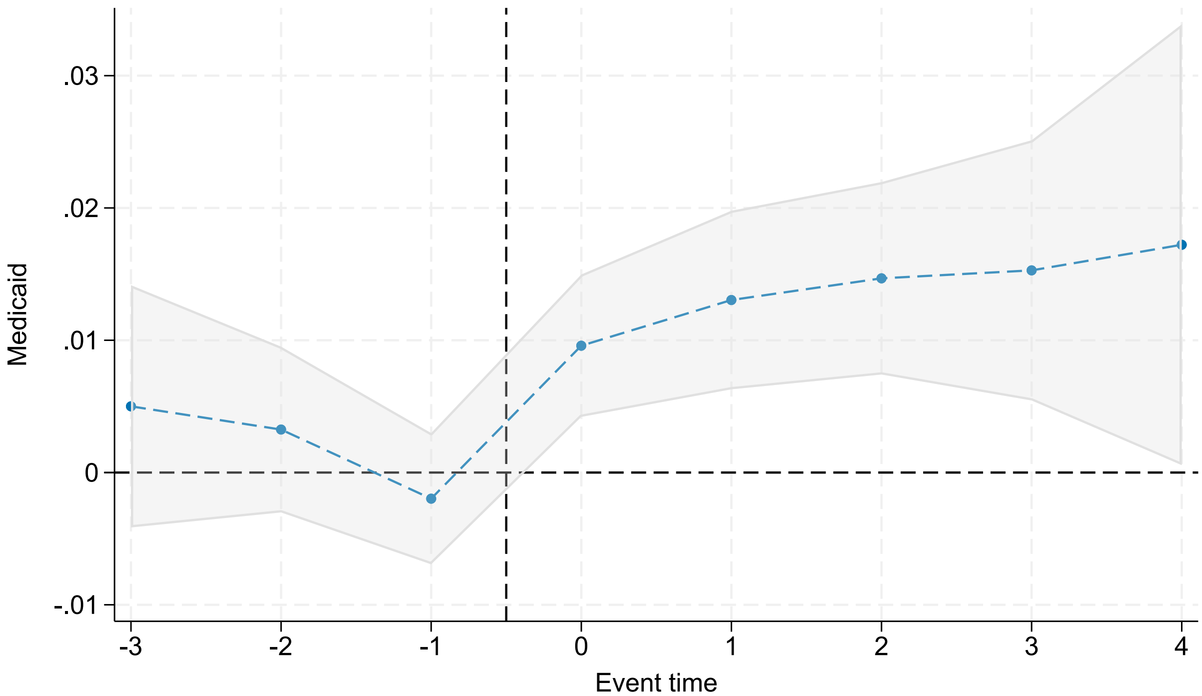

Notes: This map shows county-level social exposure to 2014–2016 Medicaid expansions in non-expansion states. Quartiles of social exposure calculated within state, with the fourth quartile representing the highest exposure.

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



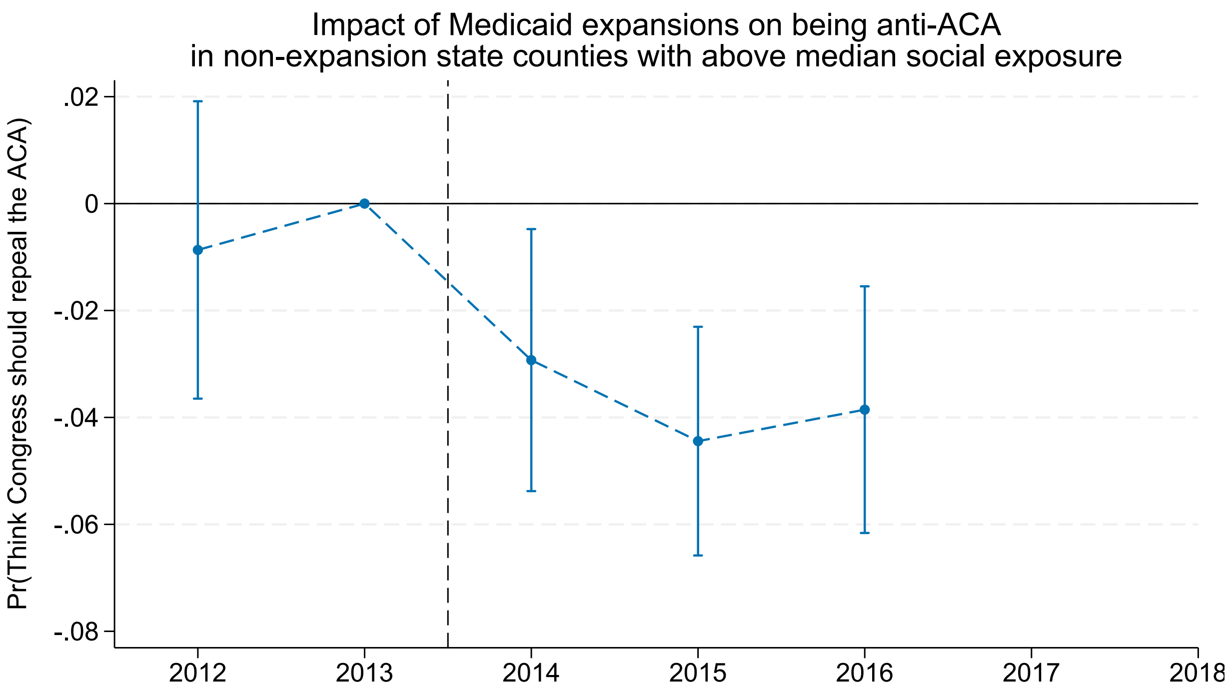

Notes:

Figure 6: Event study for impact of above-median social exposure to Medicaid expansions on insurance coverage in non-expansion states, potentially eligible adults ages 26–64 in 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 7: Impact of above median social exposure to Medicaid expansions on county-level approval of the ACA




Notes:

# 8 Tables

Table 1: 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 | Medicare | Other public | Employer | Other private | Any insurance |
| | (1) | (2) | (3) | (4) | (5) | (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 2: 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 3: 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 4: Effect of social exposure to Medicaid expansions on support for the Affordable Care Act, American adults in non-expansion states, 2012-2018

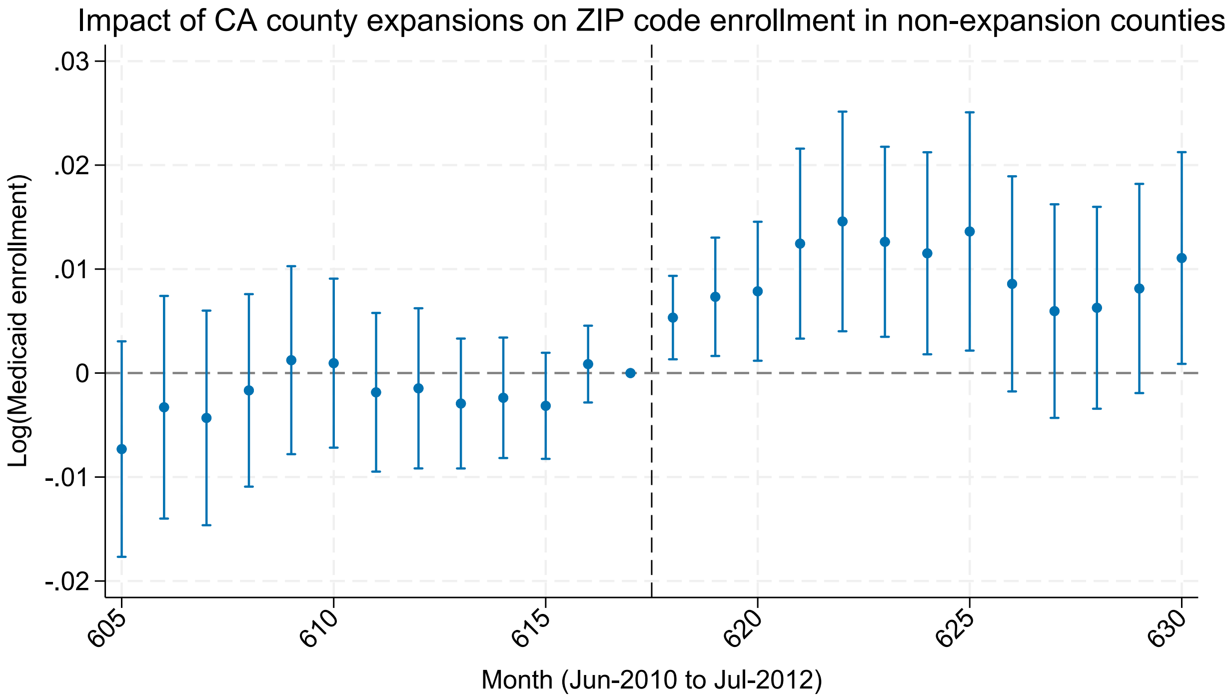
| | Pr(Support the ACA) | |
|---|---|---|
| | (1) | (2) |
| Social Exposure (county) | -0.014 | 0.024*** |
| | (0.011) | (0.009) |
| Income # Social Exposure (county) | | |
| 20k-50k | 0.027*** | |
| | (0.007) | |
| 50k-80k | 0.033*** | |
| | (0.008) | |
| 80k-120k | 0.051*** | |
| | (0.008) | |
| 120k+ | 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 status, parental status, household income, health insurance status, and political party.

# 9 Supplemental Exhibits

Figure S1: Event study for impact of above-median social exposure to California county Medicaid expansions on ZIP code-level enrollment




Notes:

Table S1: 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 | Percent of network | Network's elig. thresh. |
| Social Exposure | 0.008*** | 0.006*** | 0.069*** | 0.052*** |
| | (0.002) | (0.002) | (0.019) | (0.016) |
| PUMA fixed effects | Y | Y | Y | Y |
| State-year fixed effects | Y | Y | Y | Y |
| Income controls | Y | Y | Y | Y |
| R-squared | 0.055 | 0.055 | 0.055 | 0.055 |
| Outcome mean, 2012-13 | 0.227 | 0.227 | 0.227 | 0.227 |
| Number of PUMAs | 911 | 911 | 911 | 911 |
| Number of observations | 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 6. 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 S2: Effect of exposure to Medicaid expansions using birthplace as proxies for social connection, potentially eligible Americans ages 27-64 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 S3: Effects of subgroup-specific social network exposure on Medicaid enrollment, potentially eligible Americans ages 27-64 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 S4: Effect of social network exposure to Medicaid expansions on Medicaid enrollment, by age, low-inc
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 6 |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| Social Exposure | 0.004 | 0.006 | -0.001 | 0.009*** | 0.008** | 0.003 | -0.00 |
| | (0.005) | (0.006) | (0.003) | (0.003) | (0.004) | (0.005) | (0.00 |
| 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 | 0.07 |
| Outcome mean, 2012-13 | 0.691 | 0.577 | 0.134 | 0.194 | 0.213 | 0.247 | 0.26 |
| 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 | 633,4 |

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