From Distant Social Ties to Local Public Benefits: The Influence of Out-of-State Social Connectedness on Medicaid Enrollment

Jack Chapel
University of Southern California[*]

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Abstract

Local social networks can influence people's engagement with public programs, but little is known about how this relationship operates more broadly in an increasingly online world, where social connections transcend physical boundaries. This paper investigates the influence of geographically dispersed social networks on local public benefits participation, using Medicaid enrollment during the Affordable Care Act (ACA) eligibility expansions as a case study. I estimate the effect of being more socially connected to states with Medicaid expansions on the likelihood of being enrolled in the program among already eligible individuals in states that opted out and left eligibility rules unchanged. I find the expansions caused a 1-2 percentage point increase in the probability of Medicaid enrollment among non-elderly adults with stronger social connections to Medicaid-expanding states, despite unchanged eligibility for themselves—a "woodwork effect." The impact on Medicaid enrollment was reflected in the total insured rate without affecting private insurance, which suggests gains in newly insured beneficiaries were the driving factor. Moreover, areas with stronger social ties to Medicaid-expanding states also exhibited increased support for the ACA following the expansions. The results highlight the importance of social connections across broad geographic space in shaping local economic behavior, which can lead to unforeseen spillovers resulting from distant policy changes.

[*]Department of Economics, University of Southern California, Los Angeles, CA.

1 Introduction

Take-up of public benefits tends to be well below full enrollment in the United States and most developed countries. A long-standing research question has been why so many individuals who are eligible to receive public benefits do not take advantage of them, with evidence pointing to barriers such as information frictions, stigma, and administrative burdens as important (Ko and Moffitt, 2022). Research suggests people's social networks can influence their engagement with the public benefits system by, for example, providing new information or reducing stigma. However, most of this research has focused on very close social ties, such as to neighbors or family members (Chetty et al., 2013; Bertrand et al., 2000; Aizer and Currie, 2004; Dahl et al., 2014a)—little is known about the influence of broader, geographically dispersed social networks (Wilson, 2022).

As social and economic behavior increasingly takes place online, interactions across large geographic spaces are more common and consistent. Today, dispersed social networks connected online can be nearly as influential in people's lives as their local community, including influencing their economic behavior (Kuchler et al., 2022). To what extent do these geographically distant networks impact individuals' engagement with local public benefits? The answer is important for understanding how and when people interact with public benefits systems, designing interventions to promote take-up among the eligible, and assessing the potential for policy spillovers from changes in other states.

I explore this question in the context of Medicaid, the United State's public health insurance program for the low-income population and one of the largest public benefits programs in the country in both spending and enrollment [cite]. Medicaid take-up rates tend to be relatively low, especially for adults. For example, Decker et al. (2022) estimate the participation rate among eligible adults was 44%–46% in 2014–2017. Although some of these non-enrolled eligibles are able to get coverage elsewhere, the uninsured rate for this group remains high—14% in 2018 (Blumberg et al., 2018)—despite the availability of free or near-free coverage. Evidence suggests potential barriers to enrollment include information (Aizer, 2007; Desmond et al., 2016; Kenney et al., 2015; Wright et al., 2017), stigma (Stuber and Schlesinger, 2006; Allen et al., 2014), and administrative barriers (Bansak and Raphael, 2007; Fox et al., 2020; Wu and Meyer, 2023). Helping eligible people overcome potential barriers to take-up is important for achieving universal health coverage, which has remained distinctly elusive in the United States relative to other developed nations.

I study the extent to which individuals who are eligible for Medicaid but not enrolled can be induced to take-up coverage when they are socially exposed to newly enrolled beneficiaries through their out-of-state friend networks. Social exposure to Medicaid through friends could impact enrollment through multiple channels:

- Information — Social exposure to Medicaid expansions could improve one's own information about the program. As eligible people's out-of-state friends either become newly eligible and enrolled or otherwise learn more about the program, they themselves might become aware of the program and their eligibility or learn new information that facilitates access.

- Stigma — Models of stigma in welfare programs typically incorporate the influence of observing others. As people see (via their online/geographically distant social networks) more people like them engaging with Medicaid, they might become more comfortable with the idea of taking the benefit themselves.

- Population support and administrative burden — In addition to influencing potentially eligible individuals' behavior directly, social network exposure could have a broader county-level impact as the general population also learns more about the program. If the general population becomes more supportive of Medicaid as a result of learning about out-of-state experiences through their social networks, then this could spur improved local administration of and advocacy for the program; on the other hand, if the general population becomes less supportive and lead to worse administrative barriers. Medicaid is a Federal-State-Local partnership, and local (e.g., county) governments often play important roles in administration (National Association of Counties, 2023).

To analyze the effects of social exposure to new Medicaid beneficiaries I leverage variation in state Medicaid eligibility expansions following the Affordable Care Act of 2010 (ACA). A major provision of the ACA was expanding Medicaid eligibility rules to include all low-income adults below 138% of the Federal poverty line. Since Medicaid previously mostly covered low-income children, very low-income parents, disabled, and elderly, this change precipitated a large increase in the number of beneficiaries. However, due to a Supreme Court ruling allowing states to opt out of expansion, only about half of states expanded their Medicaid eligibility in 2014 while others kept eligibility the same.

Although there was no direct eligibility change in the states that didn't expand, this policy change could have had unanticipated spillovers. Indeed, researchers have documented increases in Medicaid enrollment among individuals that were already eligible under pre-expansion rules—dubbed the "woodwork" or "welcome mat" effect (Frean et al., 2017; Currie and Duque, 2019)—including in states that did not expand Medicaid. Yet, little is known about the mechanisms underlying this effect, and evidence is particularly lacking for the extent of the woodwork effect in non-expansion states. To what extent might this spillover be driven by individual's social connections?

Among those in non-expansion states, already eligible individuals had different degrees of social connection to the expansion states. Given the differential pre-existing social connectedness to expansion states, the ACA policy change created a large shock to individuals' exposure to Medicaid through the experiences of their distant social networks even though there were no changes to Medicaid in their own state. I exploit the within-state variation in this social exposure shock to estimate the effect of having friends exposed to Medicaid expansions on one's own likelihood of engaging with the program. I use the Facebook county-to-county Social Connectedness Index (SCI) (Bailey et al., 2018a) to proxy for social connections to Medicaid expansion states among counties in non-expansion states.

I find that potentially eligible non-elderly adults in areas with stronger social connections to Medicaid expansion states were 1-2 percentage points more likely to be enrolled in Medicaid after the 2014 ACA expansions—even though eligibility did not change for these individuals—compared to other residents of the same state but living in areas with less connections to expansion states. The effect on Medicaid enrollment is reflected in the total insured rate while the probability of being covered by private insurance does not change, suggesting the results are driven by otherwise uninsured individuals becoming newly insured. I confirm these results are not driven by differential pre-trends or biases resulting from the two-way fixed effects with staggered adoption study design by applying methods from Callaway and Sant'Anna (2021) in an event study framework.

Another potential threat to my identification strategy is the possibility that contemporaneous shocks that are correlated with the treatment and outcome are occurring. For example, if there are other local-level Medicaid enrollment campaigns occurring around this time and these campaigns are more likely to be in areas with more social connections, then I might attribute their impact to social connectedness. To address this concern I employ a second strategy in which I use the birthplace of individuals and their fellow household members to proxy for social connections to Medicaid expansion states. If some people within the same area are born in a different state, they are more likely to have a social connection to that state. In the most stringent specification I include PUMA-year fixed effects to compare individuals within the same PUMA and with the same eligibility but different degrees of connection via birth state to Medicaid expansions. I similarly find individuals with stronger social connections to expansion states increased probability of being enrolled in Medicaid by 1-2 percentage points following the 2014 Medicaid expansions.

To begin to explore the potential channels through which social exposure to Medicaid expansions is operating on enrollment, I construct alternative versions of the social connectedness variable. First, I examine the extent to which the effect might be driven by friends just across the border in an expansion state. I create versions of social connectedness that exclude friends living within 100 and 200 miles. The effects with these alternatively constructed social exposure remain significant and similar in magnitude, although it shrinks some when excluding friends within 200 miles. Next, I create versions of social connectedness specific to certain language groups based on respondents' reported main language spoken at home. I find exposure to expansions through these language-specific social connectedness measures only impact members of their language group and are additive to the overall social connectedness effects.

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. 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 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. 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. 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.

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

My results contribute to a few strands of literature. The issue of incomplete participation in public benefits programs among the eligible has long been of interest to economists (Moffitt, 1983; van Oorschot, 1996; Ko and Moffitt, 2022; Janssens and Van Mechelen, 2022). A large literature has studied potential barriers and facilitators to program take-up (see Ko and Moffitt (2022) and Janssens and Van Mechelen (2022) for reviews) and tends to center around the themes of information frictions (Kenney et al., 2015; Stuber et al., 2000; Figlio et al., 2015), stigma (Moffitt, 1983; Stuber and Schlesinger, 2006; Celhay et al., 2022), and administrative burden (Herd and Moynihan, 2019). A number of studies have examined these factors within the context of Medicaid participation (see section 2.2 for a full discussion). Information frictions and administrative burdens appear to be key barriers in the Medicaid context (Kenney et al., 2015; Stuber et al., 2000; Aizer, 2007; Bansak and Raphael, 2007; Fox et al., 2020; Ericson et al., 2023). Behavioral factors like complexity, procrastination, and salience of future benefits can also be important (Baicker et al., 2012; Wright et al., 2017). On the other hand, Stuber et al. (2000) and Stuber and Schlesinger (2006) have found stigma is less important as a barrier in Medicaid than in other welfare programs.

One determinant of Medicaid take-up with particular policy interest is the so-called "woodwork effect," a 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 (see section 2.2 for a full discussion). Some evidence has suggested the woodwork effect from Medicaid expansions can be substantial (Sonier et al., 2013; Frean et al., 2017), while others have found smaller impacts, particularly for children of new adult beneficiaries (Hudson and Moriya, 2017; Hamersma et al., 2019; Sacarny et al., 2022; Sommers et al., 2012). However, there is little evidence regarding the mechanisms of the woodwork effect. Moreover, limited evidence suggests a woodwork effect occurred in the non-expansion states after the ACA Medicaid expansions (Frean et al., 2017), and less is known about the extent and cause of this impact in the non-expansion states. I fill this gap in the literature by providing evidence that a woodwork effect occurred in the non-expansion states, operating through existing social networks.

Researchers have studied how social interactions within one's peer networks can influence barriers and potentially lead to improved enrollment, for social benefits programs generally and for Medicaid in particular, by increasing information, reducing stigma, or helping overcome burden. In early work, Bertrand et al. (2000) estimated the importance of network effects in welfare participation by asking whether being surrounded in an MSA by members of the same language-speaking group increased welfare participation more for those from language groups with higher average participation. Using similar strategies, Aizer and Currie (2004) examined the impacts of within racial/ethnic group participation in public pre-natal care, this time using ZIP to more finely proxy for local networks. They found high within-group correlations in participation, but cast doubt on the idea they are a result of information sharing. More recently, Grossman and Khalil (2020) investigated the impact of local neighborhood networks on pregnant women's' participation in Medicaid and find that those living on census blocks with a higher share of previously pregnant Medicaid participants increased currently pregnant women's' participation. And in influential work, Chetty et al. (2013) use local (ZIP code) level variation in the extent of self-employment income reporting manipulation to optimize EITC refunds as a proxy for local network knowledge on the program; they find it is important for claiming.

These studies are limited in that they rely on very local areas, often paired with racial/ethnic groups, to proxy for social networks. While important, these local-level networks are only part of an individuals social network, and little is known about how broader networks that are likely becoming more important in the digital age might operate. A few studies have begun to extend beyond the local neighborhood to examine the impact of coworkers and schoolmates (Dahl et al., 2014b; Markussen and Røed, 2015). I add to this literature by providing evidence that geographically distant social networks can impact program participation in similar ways to local ones.

Only one other study has similarly examined the importance of geographically distant social networks on public program participation; Wilson (2022) uses a similar strategy to mine to estimate the impact of out-of-state implementations of state EITC policies on EITC filing behavior, using the Facebook SCI as a proxy for social networks. The author finds individuals in counties with stronger social connection to states with a new EITC change their filing behavior to further maximize their benefits, but it does not impact the likelihood of participation in the program. My findings differ in that I do find a change in program participation, which could be due to a few differences. A main difference is that the EITC is a tax-filing-based program, which might be subject to less stigma concerns and could have streamlined participation while individuals are already filling out taxes, compared to the application-based Medicaid, which might be subject to more information, stigma, and administrative barriers. Second is that baseline participation in the EITC is already much higher than for Medicaid, which could be a reflection of the aforementioned tax- vs. application-based implementation, leaving less room for improvement.

My work also contributes to a growing literature on the impacts of geographically distant social networks more generally, particularly for financial decisions (Kuchler and Stroebel, 2021). 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 participation as an economic behavior that can be influenced through social networks.

Finally, my findings that areas with more social connection to the Medicaid expansions exhibited changes in their policy preferences contributes to a literature on policy diffusion (Linos, 2013). In addition to studying the diffusion of new policies across countries, this literature has examined how the United States operate as laboratories of democracy and how policy innovations can transmit across states Shipan and Volden (2008); Gray (1973); Walker (1969). 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.

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

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

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 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 could help (Wright et al., 2017).

Of particular interest to policy-makers, especially during the ACA Medicaid expansions, is the "woodwork" or "welcome-mat" effect. 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.

Frean et al. (2017) estimated that one half of the Medicaid enrollment gain in 2014–15 could be explained by previously eligible individuals enrolling, including some individuals in non-expansion states. Hamersma et al. (2019); Hudson and Moriya (2017) similarly find woodwork effects from the Medicaid expansions on participation among new beneficiaries' children, although the magnitude is not as large. Sacarny et al. (2022) use randomization from the Oregon Medicaid experiment and find only small woodwork effects for children becoming enrolled when their parents become new beneficiaries. Frean et al. (2017) suggest the woodwork effect might have occurred in non-expansion states as well, but little is known about the extent of causality and the potential mechanisms.

3 Theoretical Background: The Take-Up of Public Benefits

Will be added in next draft.

4 Data

4.1 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.

4.2 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.

4.3 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.

5 Empirical Strategies

I first establish the extent of the increase in Medicaid enrollment following the ACA Medicaid expansions. I estimate the impact of the expansions on Medicaid enrollment and total insurance coverage in the expanding states and benchmark my estimate against other prominent figures in the literature. Then, I estimate the spillover effects the expansions had in non-expansion states through people's social networks.

5.1 Estimating Direct Effects of Medicaid Expansions

I start by estimating the direct effects of Medicaid expansion on enrollment and insurance coverage in the expanding states in a difference-in-differences (DiD) framework. Figure 3 shows there was a relatively sharp increase in enrollment among low-income, non-elderly adults in expansion states after 2014. I estimate two-way fixed effects (TWFE) models with pooled cross-sections of ACS data and using PUMAs as the main geographic unit for analysis. Specifically, for individual i living in PUMA p in year t, I estimate

$$Y_{ipt} = \alpha + \beta MedicaidExpanded_{s(p),t} + X_{it}'\Gamma + \mu_p + \lambda_t + \varepsilon_{ipt}. \tag{2}$$

Y_{ipt} is a binary indicator for individual i being covered by Medicaid and X_{it} include controls for individual characteristics such as age, sex, race, and employment. μ_p are PUMA fixed effects, which absorb any unobserved time invariant characteristics that might be related to Medicaid enrollment. λ_t are year fixed effects, which absorb national level shocks that could impact enrollment, such as other federal changes in health insurance requirements like the individual mandate. $MedicaidExpanded$ is an indicator equal to 1 if the state PUMA p is a member of has expanded Medicaid as of year t, and β is the coefficient of interest measuring the effect of expansion on the probability of being enrolled in Medicaid.

Identification requires the assumption that Medicaid enrollment in expansion states would have evolved similarly to that in non-expansion states had the expansions never occurred. I start with the assumption there are no spillovers and the non-expansion states serve as valid counterfactual trends for how the expansion states would evolve in the absence of treatment, following many other studies using Medicaid expansions in a DiD study design. If the Medicaid expansions also affect enrollment in non-expansion states then the stable unit treatment value assumption required of the generalized fixed effects framework will be violated. Figure 3 shows there was a slight increase in enrollment the non-expansion states after 2014. The increase in non-expansion states could imply the existence of spillover effects or be caused by broader national trends (e.g., changing economic circumstances). I return to the issue of potential biases resulting from social spillovers in section 7.

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.

5.2 Estimating Indirect Social Exposure Effects

After documenting the increase in Medicaid enrollment directly caused by the 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. To proxy for social connectedness I use the Facebook SCI, described in section 4.2. 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:

$$SocialExposure_{p,t} = \sum_{q} w_q \cdot SCI_{p,q} \cdot MedicaidExpanded_{s(q),t}, \tag{3}$$

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

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

The coefficient of interest, β, is the effect of a 1 standard deviation increase in social exposure to Medicaid expansions on Y, the probability of being enrolled in Medicaid. μ_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.

As noted above, TWFE designs with staggered adoption can have significant biases in the presence of treatment effect heterogeneity. Moreover, my treatment of interest in this case, $SocialExposure$, is a continuous measure, which can cause further issues (Callaway et al., 2021). To address these issues, I convert $SocialExposure$ to a binary treatment and employ the same doubly-robust augmented inverse-probability weighting estimation procedures as above (Callaway and Sant'Anna, 2021). Specifically, I calculate the within-state median value of $SocialExposure$ in 2018 and treat a PUMA as treated when it surpasses this median value. As a result, half of the PUMAs within each state are "never treated" and serve as clean controls for the other half.

5.2.1 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

$$Y_{ipt} = \alpha + \beta BirthStateExpanded_{s(i),t} + X_{it}'\Gamma + \mu_{p,s(i)} + \lambda_{p,t} + \varepsilon_{ipt}. \tag{5}$$

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.

5.2.2 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

6 The Direct and Social Network Impacts of Medicaid Expansions

6.1 Direct Effects of Medicaid Expansions on Enrollment in Expansion States

The direct effects of Medicaid expansions on enrollment in the expansion states are shown in Table 1. The expansions caused a 13 percentage point increase in the enrollment rate among adults ages 27-64 under 138% of the federal poverty line, the most likely to newly benefit from the expanded eligibility. Childless, non-disabled adults ages 18-26 were also newly eligible, but they also benefited from changes to private insurance which required they be eligible for coverage as a dependent under their parents' health insurance plan. In addition to their wider set of potential options, this younger and relatively more healthy age group is likely less inclined to seek out coverage in the first place. These potential factors are reflected in the magnitude of effect of the expansions on their enrollment, which is about half as large as it was for Americans ages 27–64.

Eligibility did not change for the under age 18 and ages 65-plus groups. However, I estimate small enrollment increases of about 1 percentage point for these groups as a result of the Medicaid expansions, consistent with the woodwork effect hypothesis.

I estimate the Medicaid expansions increased total insurance coverage by 4 and 8 percentage points in the ages 18–26 and 27–64 populations, respectively, indicating the majority of the new Medicaid enrollment were newly covered beneficiaries who would have otherwise been uninsured. I find no effects on the insured rate for children or older Americans.

To address the known issues with TWFE designs with staggered adoption I estimate aggregated ATETs following Callaway and Sant'Anna (2021) in Figure 4. The estimates suggest differential pre-trends driving results is not a concern, and the estimated impact grows over time to about a 15 percentage point increase in enrollment after two years of expansion.

My estimates for the effects on Medicaid enrollment and the insured rate are in approximate alignment with prominent estimates from the literature. Miller and Wherry (2019) estimate that four years after expansion, low-income adults in expansion states were 17 percentage points more likely to be enrolled in Medicaid and 12 percentage points less likely to be uninsured. Courtemanche et al. (2017) estimate the ACA increased the overall insurance rate by 5.9 percentage points for residents in expansion states versus 2.8 percentage points in non-expansions states, a comparative gain of just over 3 percentage points, which is similar to the pooled average of gains by age-group I estimate.

6.2 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 3 shows results from estimating equation (4) 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 4 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.

6.2.1 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 5 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.

6.3 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 8 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.

7 Implications

[Potential sections to add — analyses not yet completed]

7.1 Public Expenditures Resulting from Social Spillovers

A major reason many states cited for not expanding Medicaid under the Affordable Care Act was the potential for added state fiscal burdens as a result of the "woodwork effect" wherein previously eligible individuals—who would not be covered by the 90%–100% Federal funding coverage for the new expansion beneficiaries—learn about Medicaid and become enrolled, increasing the number of Medicaid enrollees drawing from tight state budgets. This argument was made under the assumption that the woodwork effect would operate through local networks and from the states' own expansion of Medicaid, but inter-state network effects were not considered. Using county-level Medicaid expenditures data, I instrument for Medicaid enrollment using social exposure to Medicaid expansions to estimate the implied effect of this woodwork effect on state budgets.

7.2 Policy Diffusion Through Social Networks

The results suggest broader impacts on support for the program beyond those potentially eligible, which could impact enrollment through overall support for the program and improvements to it at the local level. Did this impact future expansions of Medicaid? Following the initial set of state expansions in 2014–2016 there was a lull in states expanding the program until the 2020s, when multiple states expanded via ballot initiative rather than legislation introduced by state lawmakers. I estimate the effect of social exposure to 2014–2016 expansions on precinct-level voting outcomes for the state ballot initiatives in recent years.

7.3 Estimating Medicaid Expansion Impacts in the Presence of Social Spillovers

8 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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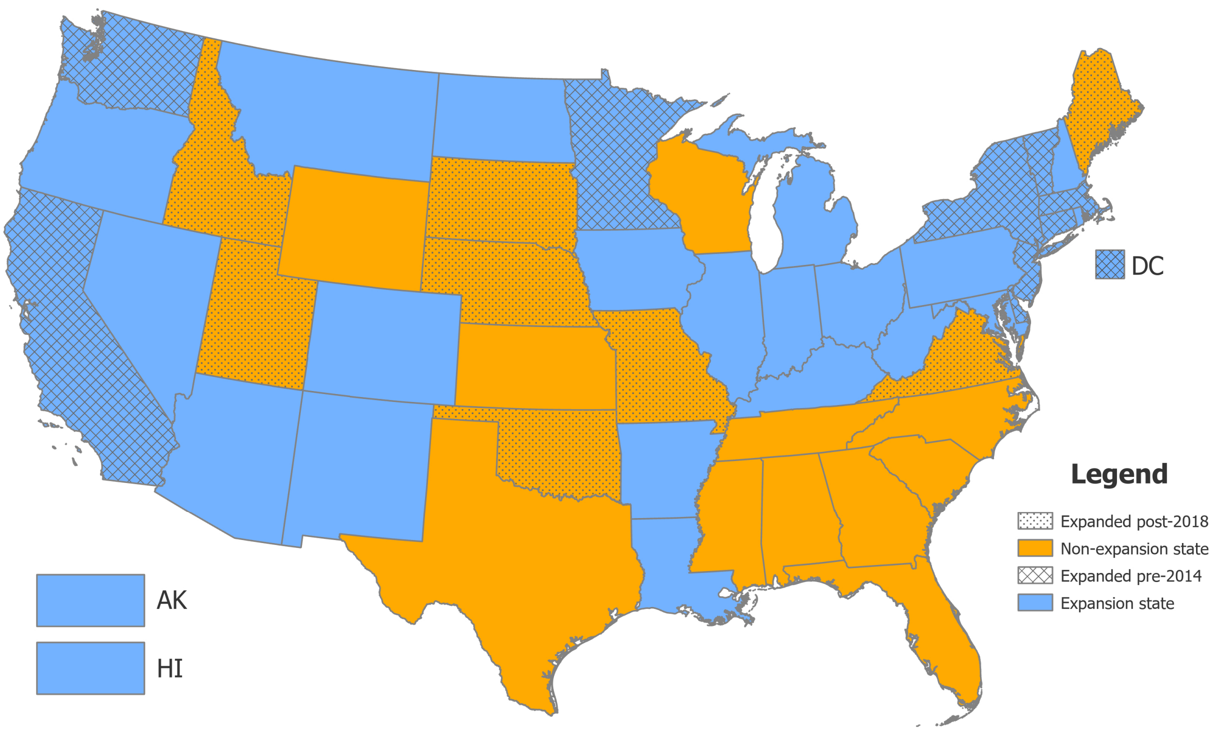
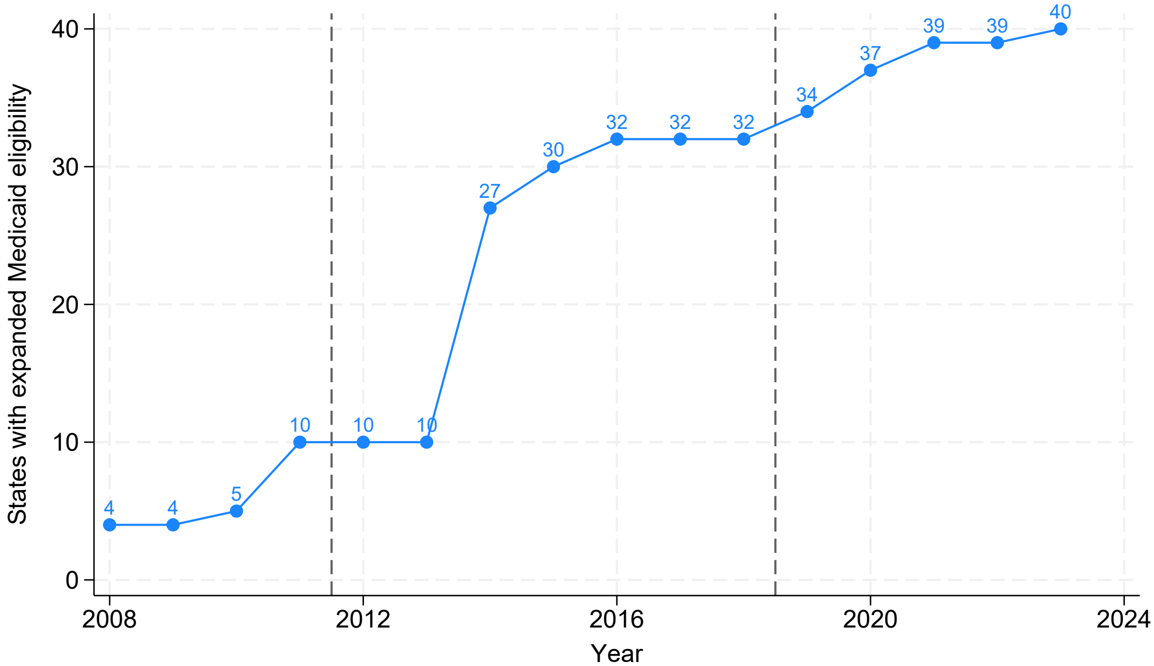
9 Figures

Figure 1: States' ACA Medicaid expansion status in 2018



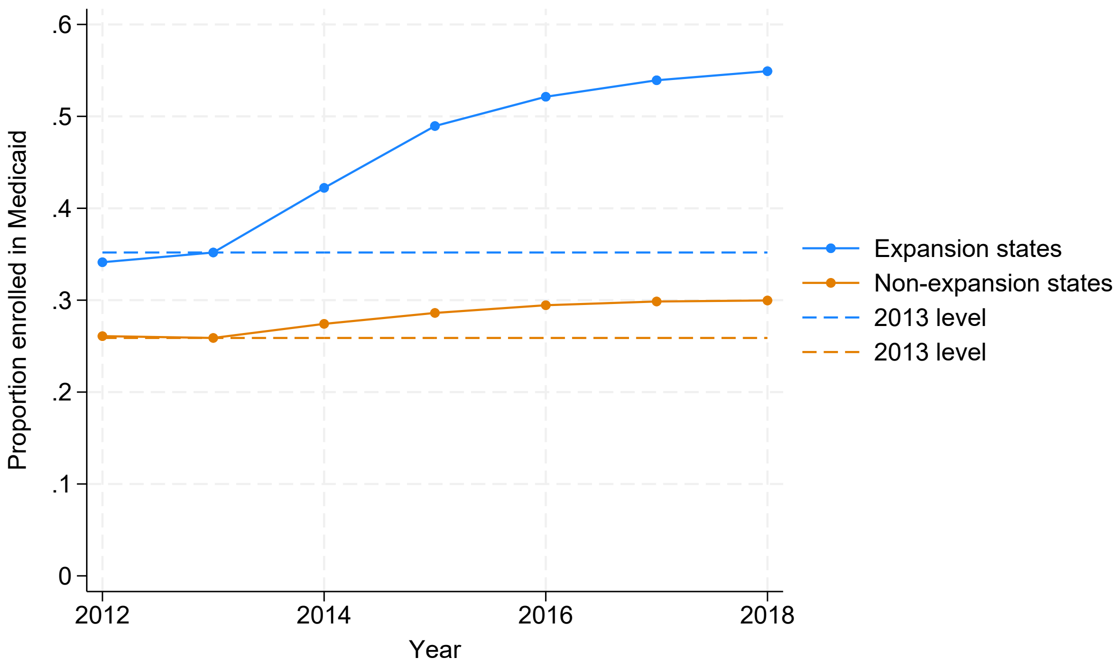
Notes: This map shows states' Medicaid expansion status—extending eligibility to all low-income (<138% poverty) adults—as of 2018. States with Medicaid programs that covered all low-income adults before the 2014 ACA expansions are defined as already expanded. Data come from the Kaiser Family Foundation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



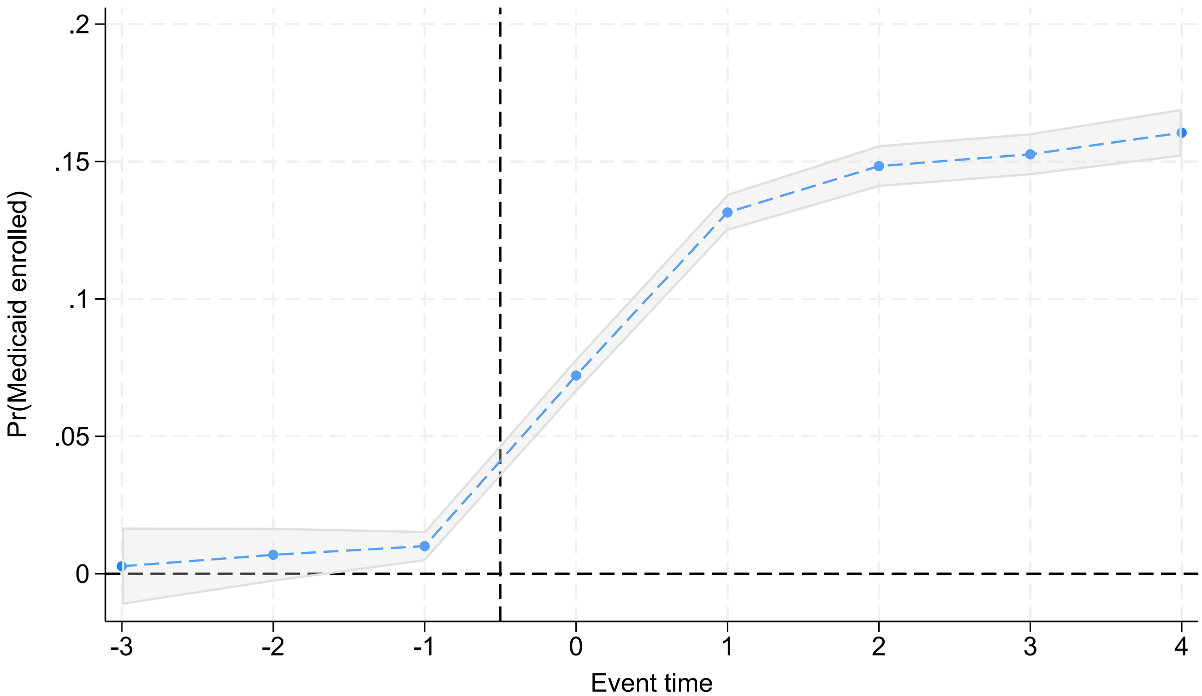
Notes: This figure shows the trend in the number of states that had expanded Medicaid to cover all low-income (<138% poverty) adults. States with Medicaid programs that covered all low-income adults before the ACA expansions are defined as expanded; early expanding states are described in the notes to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

Figure 3: Medicaid enrollment rate trends in expansion and non-expansion states, low-income adults ages 18–64 in 2012–2018



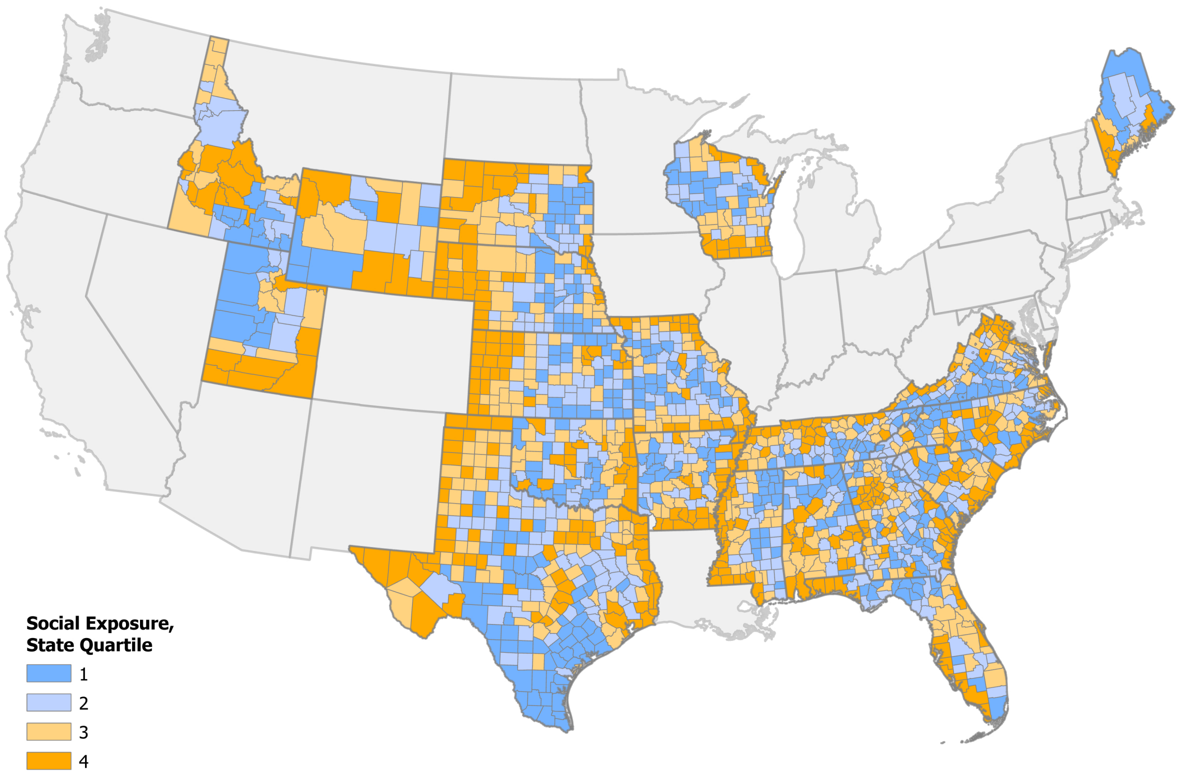
Notes: This figure shows trends in the proportion of low-income (<138% poverty) adults enrolled in Medicaid in expansion and non-expansion states. Dashed lines show the proportion enrolled in 2013 for reference.

Figure 4: Event study for impact of Medicaid expansions on enrollment in expansion states, low-income adults ages 27–64 in 2012–2018



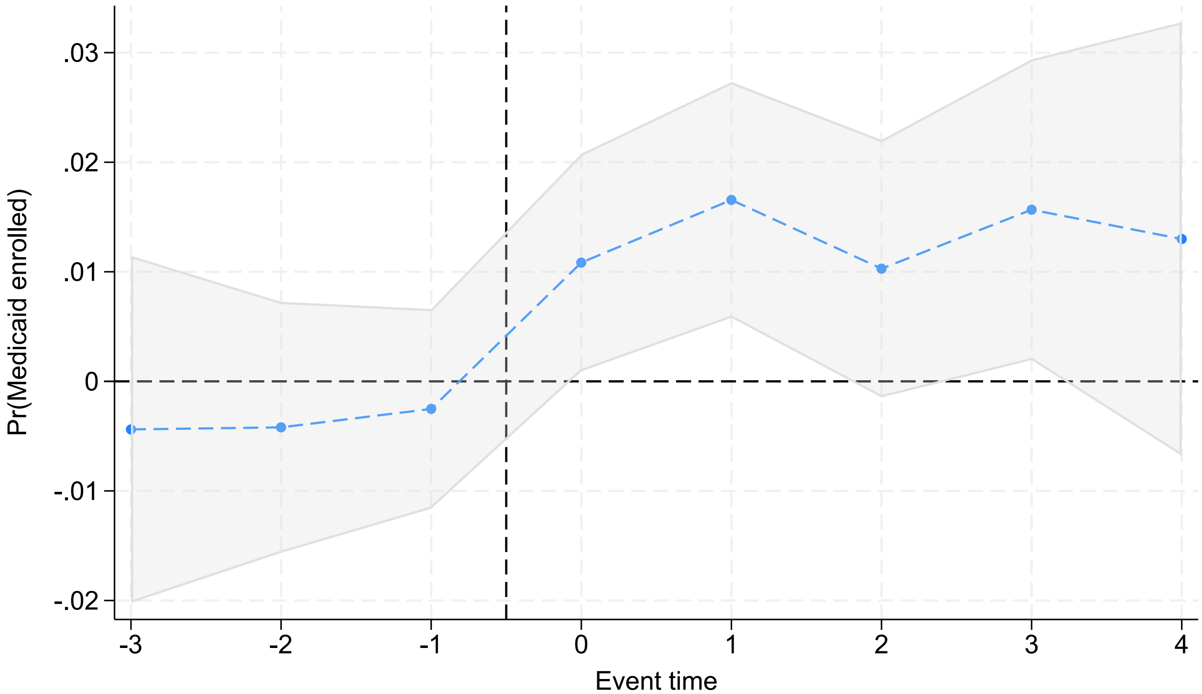
Notes: This figure shows the dynamic average treatment effects on the treated for the impact of Medicaid expansions on the probability of enrollment using the augmented inverse-probability weighting estimation procedures in (Callaway and Sant'Anna, 2021). Controls in both the outcome and selection equations 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 5: 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 6: Event study for impact of above-median social exposure to Medicaid expansions on insurance coverage in non-expansion states, potentially eligible adults ages 27–64 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.

10 Tables

Table 1: Effect of ACA Medicaid expansions on health insurance coverage in expansion states, low-income Americans, 2012-2018

	Effect on health insurance coverage among:			
	Age <18	Age 18-26	Age 27-64	Age 65+
Panel A: Effect on Pr(Medicaid)				
State Medicaid expanded	0.011***	0.068***	0.127***	0.012***
	(0.003)	(0.003)	(0.003)	(0.003)
Individual controls	Y	Y	Y	Y
PUMA fixed effects	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y
Outcome mean	0.761	0.190	0.359	0.328
R-squared	0.066	0.178	0.152	0.066
Number of PUMAs	1,676	1,676	1,676	1,676
Number of observations	1,081,222	1,077,553	1,733,269	724,064
Panel B: Effect on Pr(Any insurance)				
State Medicaid expanded	0.000	0.038***	0.079***	-0.000
	(0.002)	(0.003)	(0.003)	(0.001)
Individual controls	Y	Y	Y	Y
PUMA fixed effects	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y
Outcome mean	0.918	0.767	0.650	0.974
R-squared	0.043	0.148	0.130	0.067
Number of PUMAs	1,676	1,676	1,676	1,676
Number of observations	1,081,222	1,077,553	1,733,269	724,064

Notes: *** $p < .01$, ** $p < .05$, * $p < .10$. Standard errors (in parentheses) clustered at the PUMA level. Low-income defined as below 138% of the federal poverty level. Excludes states that expanded Medicaid eligibility to all low-income adults before 2014. 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 2: Summary statistics for main analysis sample, potentially eligible adults ages 27-64 in non-expansion states

	Respondents in PUMAs with social exposure to Medicaid expansions:			
	Below state median		Above state median	
	Mean in 2013	Diff., 2013–2018	Mean in 2013	Diff., 2013–2018
Age	43.1	0.71	43.0	0.76
Male	0.40	-0.006	0.38	0.003
White, non-Hispanic	0.47	-0.018	0.43	-0.013
Black, non-Hispanic	0.21	-0.000	0.30	0.006
Hispanic	0.28	0.015	0.20	0.001
Married	0.35	-0.045	0.32	-0.029
Parent	0.69	-0.029	0.70	-0.034
Disabled	0.44	0.028	0.42	0.029
Metro area	0.60	0.003	0.83	0.001
Employed	0.32	0.002	0.33	-0.001
Income as % of poverty line	47.8	-0.39	47.2	0.19
Any health insurance	0.57	0.082	0.58	0.106
Medicaid	0.38	0.041	0.37	0.053
Any private insurance	0.17	0.049	0.20	0.063

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

Table 3: Effect of social network exposure to out-of-state Medicaid expansions on Medicaid enrollment among potentially eligible Americans in non-expansion states, 2012-2018

	Pr(Medicaid)			
	Ages <18	Ages 18-64	Ages 27-64	Ages 65+
Social exposure	0.006	0.008*	0.012**	-0.007
	(0.005)	(0.005)	(0.005)	(0.008)
Individual controls	Y	Y	Y	Y
PUMA fixed effects	Y	Y	Y	Y
State-year fixed effects	Y	Y	Y	Y
Outcome mean	0.668	0.399	0.398	0.392
R-squared	0.071	0.132	0.145	0.094
Number of PUMAs	911	911	911	911
Number of observations	839,701	521,144	428,591	238,164

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, 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 4: Effect of social network exposure on health insurance coverage by source, potentially eligible Americans ages 27-64 in non-expansion states, 2012-2018

	Probability of health insurance coverage from					
	Medicaid	Medicare	Other public	Employer	Other private	Any insurance
Social exposure	0.012**	0.003	-0.002	0.006	-0.000	0.016**
	(0.005)	(0.004)	(0.002)	(0.005)	(0.003)	(0.006)
Individual controls	Y	Y	Y	Y	Y	Y
PUMA fixed effects	Y	Y	Y	Y	Y	Y
State-year fixed effects	Y	Y	Y	Y	Y	Y
Outcome mean	0.398	0.137	0.039	0.138	0.086	0.627
R-squared	0.145	0.161	0.087	0.093	0.046	0.126
Number of PUMAs	911	911	911	911	911	911
Number of observations	428,591	428,591	428,591	428,591	428,591	428,591

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. Regressions weighted using ACS person-level analysis weights.

Table 5: 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

	Pr(Enrolled in Medicaid)					
	Own birth state connection			Any HH adult's birth state connection		
	(1)	(2)	(3)	(1)	(2)	(3)
Birth state expanded Medicaid	0.015**	0.017***	0.013*			
	(0.007)	(0.007)	(0.007)			
Any HH adult's birth state expanded Medicaid				0.011*	0.014**	0.015**
				(0.006)	(0.006)	(0.007)
Individual controls	Y	Y	Y	Y	Y	Y
PUMA fixed effects	Y			Y		
State-treatment group fixed effects	Y			Y		
State-year fixed effects	Y			Y		
PUMA-treatment group fixed effects		Y	Y		Y	Y
PUMA-year fixed effects		Y	Y		Y	Y
Restrict to those born out of state			Y			Y
Outcome mean	0.398	0.398	0.327	0.398	0.398	0.327
R-squared	0.145	0.175	0.213	0.145	0.177	0.215
Number of PUMAs	911	911	911	911	911	911
Number of observations	428,591	428,363	203,576	428,591	428,437	203,596

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 6: 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					
	Subgroup:					
	Spanish speaker		Hispanic		Black, non-Hisp.	
	(1)	(2)	(1)	(2)	(1)	(2)
Subgroup member # Subgroup social exposure	0.019***	0.021***	0.017***	0.019***	0.008**	0.008**
	(0.006)	(0.006)	(0.005)	(0.005)	(0.003)	(0.003)
Subgroup social exposure	0.002	-0.011	0.000	-0.013*	0.000	-0.006
	(0.006)	(0.008)	(0.005)	(0.007)	(0.004)	(0.006)
Subgroup member	-0.103***	-0.103***	-0.160***	-0.160***	0.091***	0.091***
	(0.006)	(0.006)	(0.005)	(0.005)	(0.004)	(0.004)
Overall social exposure		0.017**		0.020***		0.014*
		(0.007)		(0.007)		(0.008)
Individual controls	Y	Y	Y	Y	Y	Y
PUMA fixed effects	Y	Y	Y	Y	Y	Y
State-year fixed effects	Y	Y	Y	Y	Y	Y
R-squared	0.146	0.146	0.143	0.143	0.137	0.137
Number of PUMAs	911	911	911	911	911	911
Number of observations	428,591	428,591	428,591	428,591	428,591	428,591

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

	Social network exposure definition				
	Baseline	Excl. friends <100mi	Excl. friends <200mi	New beneficiary exposure	Binary
Social exposure	0.012**	0.011**	0.009*	0.006*	0.010**
	(0.005)	(0.005)	(0.005)	(0.003)	(0.004)
Individual controls	Y	Y	Y	Y	Y
PUMA fixed effects	Y	Y	Y	Y	Y
State-year fixed effects	Y	Y	Y	Y	Y
Outcome mean	0.421	0.421	0.421	0.421	0.421
R-squared	0.145	0.145	0.145	0.145	0.145
Number of PUMAs	911	911	911	911	911
Number of observations	428,591	428,591	428,591	428,591	428,591

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

	Pr(Think Congress should repeal the ACA)			
	(1)	(2)	(3)	(4)
Social Exposure	-0.035***	-0.032***	-0.014	
	(0.012)	(0.011)	(0.013)	
Social Exposure (ZIP code)			-0.020***	-0.020***
			(0.006)	(0.006)
Individual controls		Y	Y	Y
County fixed effects	Y	Y	Y	
State-year fixed effects	Y	Y	Y	
County-year fixed effects				Y
Outcome mean	0.543	0.543	0.543	0.543
R-squared	0.075	0.268	0.267	0.319
Number of counties	1,459	1,459	1,369	1,286
Number of observations	108,749	108,707	106,868	105,199

Notes: *** $p < .01$, ** $p < .05$, * $p < .10$. Standard errors (in parentheses) clustered at the county level. Social Exposure defined at the county level unless otherwise noted as being ZIP code level exposure. Individual controls include age, sex, race and ethnicity, education, marital status, parental status, household income, health insurance status, and political party. Column (3) drops observations missing ZIP codes or ZIP code level exposure, and column (4) drops observations due to insufficient observations in some counties.