Friends with Benefits: Social Spillover Effects from Out-of-State Medicaid Expansions

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Abstract

Many adults are eligible for public benefits programs but are not enrolled. This paper investigates whether geographically distant social networks can facilitate take-up of Medicaid, the U.S.'s low-income health insurance program. I estimate program take-up changes resulting from increased enrollment and salience among one's friend network due to state Medicaid eligibility expansions during 2010–2018. To isolate effects occurring through social channels, I restrict analyses to states that *did not* expand their Medicaid program and compare between communities with varying degrees of social connection to the expanding states. Potentially eligible adults with stronger social ties to the Medicaid expansions were more likely to enroll in the program following the expansions, even though eligibility was largely unaffected in their own state. The increase was reflected in decreases in uninsurance rates, with no impact on other sources of insurance. In addition to impacting take-up, social network exposure to the Medicaid expansions increased support for the Affordable Care Act and Medicaid among the broader population. The results show program experiences among one's friends can improve their own program participation and highlight how policy changes can have indirect impacts propagated through social networks.

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1 Introduction

Among adults who qualify for the U.S. health insurance program Medicaid,[1] only half take-up the benefit, leaving 1 in 5 eligible adults uninsured despite the availability of free (or near free) coverage (Decker et al., 2022; Blumberg et al., 2018). Non-participation is prevalent in many public programs, with barriers such as incomplete information, program stigma, and administrative burdens potentially impeding full enrollment (Ko and Moffitt, 2022; Janssens and Van Mechelen, 2022). Lack of participation in Medicaid is particularly concerning given its size[2] and potential benefits for healthcare access (Miller and Wherry, 2019; Wherry and Miller, 2016; Baicker et al., 2013), financial well-being (Miller et al., 2021a; Hu et al., 2018), and reduced mortality (Miller et al., 2021b; Sommers, 2017; Wyse and Meyer, 2023). Understanding the barriers to Medicaid enrollment and how to overcome them is therefore essential for achieving universal health insurance coverage and improving societal welfare.

In this paper, I study the extent to which people's social networks facilitate their participation in Medicaid. Research suggests a lack of program knowledge—such as awareness of the program's existence, their own eligibility, or how to navigate program rules—is an important source of incomplete take-up, including in Medicaid (Heckman and Smith, 2004; Aizer, 2007; Stuber et al., 2000; Kenney et al., 2015b; Flores et al., 2016; Haley and Wengle, 2021). Friends are a key source of information and could play an important role in overcoming such barriers. If an eligible adult has friends who become enrolled in Medicaid or otherwise learn more about the program, natural information flows within their network might cause them to learn about their own eligibility, how to navigate enrollment, or the benefits they could receive. Friends could also serve as a more trusted information source that may be less easily substituted with other assistance providers like patient navigators, whom some might see as less trustworthy bureaucrats. On the other hand, if friends do not naturally share their program knowledge or have bad program experiences, network effects on take-up could be non-existent or even negative.

I test whether increasing Medicaid enrollment and general salience within one's friend network causes them to be more likely to enroll in the program themselves. Identifying

[1] Medicaid is the United State's public health insurance program for the low-income population. *Medicaid* is sometimes confused with *Medicare*, the health insurance program for the population ages 65+. See, e.g., Donohue et al. (2022), Currie and Duque (2019), and Buchmueller et al. (2016) for overviews of the program and its history.

[2] Medicaid is the largest means-tested program by spending and enrollment (Buchmueller et al., 2016), and it covers more Americans than any other health insurance program (Donohue et al., 2022).

causal network effects in public program participation can be challenging. Researcher have tended to rely on strategies leveraging close geographic proximity to proxy for social networks (Bertrand et al., 2000; Aizer and Currie, 2004; Chetty et al., 2013; Grossman and Khalil, 2020), but this strategy can be complicated by issues of correlated shocks or unobservables among the network, endogenous network formation and reflection problems (Manski, 1993). Moreover, small neighborhood networks are not representative of the scope of people's social ties in the modern world; today, geographically distant networks facilitated online or through other communications technology may be as influential in people's lives as their local community members. Understanding the impacts such broad networks might have on behavior and their interaction with policy is increasingly important.

To isolate the social network effects in Medicaid take-up, I estimate how people respond when their *out-of-state* friends experience a policy change that sharply increased enrollment, even though there was no such change in their own state. The analyses center around Medicaid eligibility expansions occurring during 2010–2018. A major provision of the Affordable Care Act of 2010 expanded Medicaid eligibility to include all low-income adults under 138% of the federal poverty line.[3] However, only about half of states initially implemented this expansion, resulting in large increases in the eligible and enrolled populations in some states (Miller and Wherry, 2019; Courtemanche et al., 2017) while others left their eligibility rules largely the same.

Focusing on communities (ZIP codes, counties, and Public Use Microdata Areas) within the 19 states that had not expanded Medicaid as of 2018, I estimate the effects of social exposure to the expansions. To measure social network exposure, I use the Facebook Social Connectedness Index (Bailey et al., 2018a) to capture the number of friendship links between each pair of ZIP codes. Within each non-expansion state, communities have varying degrees of social connectedness to the expanding states, measured as the number of friends living in expanding states per community resident. When some states expanded their Medicaid eligibility, communities in the non-expanding states experienced varying increases in Medicaid enrollment and general salience among their networks due to their differing social exposure. I estimate the impacts of this arguably exogenous shift in a difference-in-differences framework by comparing between communities with relatively larger shares of friends in the expanding states compared to similar communities in the same state but with fewer out-of-state friends

[3]Previously, Medicaid eligibility rules varied by state and were primarily targeted for low-income children, parents and pregnant women, people with disabilities, and long-term care in old age. Only Delaware (1996), Massachusetts (2006), New York (2001), and Vermont (2000) had state programs implemented earlier that offered coverage more broadly to include low-income childless adults.

experiencing an expansion, before and after the expansions took place.

I first estimate impacts on Medicaid take-up using ZIP code-level data from the American Community Survey, accessed through IPUMS (Manson et al., 2023). Having one standard deviation higher strength of social connection to the Medicaid expansion states caused ZIP codes to experience a 1.5% increase in the scaled number of non-elderly adult (ages 18–64) Medicaid enrollees[4] —even though eligibility was largely unchanged in their state—compared to other ZIP codes in the same state but with less strong social connection to the expansion states. I similarly estimate the insured rate among non-elderly adults under 200% and 138% of the poverty line increased by 0.37 percentage points (0.65% of the baseline mean) and 0.58 percentage points (1.1% of the baseline mean).

The ACS ZIP code data provides high geographic granularity to utilize the most detailed Social Connectedness Index data available, but it comes with the trade-off of less ability to customize the analysis sample and has lower temporal frequency than other potential options. To examine dynamic effects over time, assess potential pre-trends, and investigate effect heterogeniety, I next turn to the ACS microdata (Ruggles et al., 2023). The benefit is that the microdata are available annually for over 3 millions respondents with detailed demographic and economic information, allowing me to more precisely identify potential beneficiaries and explore differences by individual characteristics. The trade-off is that I sacrifice geographic granularity and instead aggregate ZIP code SCI to Public Use Microdata Areas (PUMAs), the smallest geographic unit available in the microdata.[5]

Low-income adults in PUMAs with stronger social connections to the Medicaid expanding states were more likely to enroll in Medicaid after the expansions compared to those in PUMAs in the same state but with less connection to the expansions. Specifically, a one standard increase in friends per person in Medicaid expansion states increased the probability of take-up among potentially eligible low-income adults (parents and people with disabilities) by 0.7 percentage points.

[4]ZIP code data from the American Community Survey is published as 5-year pooled estimates. I use data from the 2008-12, 2009-13, 2014-18, and 2015-19 periods. Since Medicaid enrollment is only published as ZIP code population counts for selected age groups, I scale Medicaid enrollment by the under 200% poverty line population rather than a take-up rate. The ACS does publish rates of any insurance for selected age groups and income levels, which I use as additional outcomes.

[5]Public Use Microdata Areas are statistical geographic areas created by the Census and are the smallest geographic unit available in the American Community Survey while covering the entire United States. They are created to partition the United States into geographic areas that are as small as possible while containing enough people to avoid privacy and disclosure concerns. There are 2,378 PUMAs (2010 delineation), compared to 3,143 counties. In urban areas, they can be smaller than counties, and in sparsely populated areas they tend to be larger than counties.

To view dynamics over time and assess potential pre-trends, I implement an event study specification that compares PUMA with above vs. below their state's median social exposure to the expansions.[6] The event study shows no evidence of differential pre-trends, and there is a sharp increase that persists for at least two years after social exposure to expansion. The annual PUMA estimates have a time varying treatment, I further show that estimates are robust to using methods from Callaway and Sant'Anna (2021) to address concerns resulting from two-way fixed effects regressions with staggered treatment adoption.

The changes could result from people who would otherwise not have any insurance, or there could be crowd out of other sources such as employer sponsored health insurance. I similarly estimate the impacts of PUMA social exposure to Medicaid expansions on overall insurance and individual insurance sources among potentially Medicaid eligible low-income adults. I do not find effects on insurance sources including Medicare, other public, employer sponsored, and other private, and I find a positive effect on the probability of any insurance coverage that is similar in magnitude to the effect on Medicaid. This evidence is suggestive that the effects are drive by individuals gaining new coverage rather than switching coverage sources.

The American Community Survey data provides respondents' self-reported coverage by Medicaid, which could be subject to measurement errors from misreporting. In a second setting, I utilize administrative enrollment data from California's Medicaid program, which reports monthly enrollment counts at the ZIP code level. California implemented an early Medicaid expansion beginning in 2011 and rolled out at the county level. In a similar strategy, I estimate event studies comparing ZIP codes in non-expanding counties but with differential exposure to Medicaid expanding counties. I focus on the initial round of expansions in July 2011, which included some large counties like Los Angeles. I find that ZIP codes with above median social connection to the expansion counties exhibited 1-2% higher Medicaid enrollment following the expansions compared to those with below median social network exposure. In addition to confirming the results not due to misreporting, these estimates show the results may generalize beyond the specific context of the 2014–16 expansion period.

A final validity concern is the possibility that contemporaneous, correlated shocks could occur even at the ZIP code level. As another robustness check, I next consider a different proxy for one's social network: their state of birth. People born in a different state are more

[6] Most of the initial expanding states implemented the expansion in 2014, but some expanded in 2015 and two expanded in 2016. I measure the state median in 2018 (i.e., median among exposure to all expansion states) and I consider a PUMA treated in the year its social exposure to states that had expanded Medicaid by that year reached above the state median. Therefore, treatment is time varying.

likely to have social connections to that state than other residents in their neighborhood born in other states. Now, the comparison is between individuals living within the same PUMA but born in different states. The identifying assumption is that individuals living within the same PUMA would have the same evolution of Medicaid take-up over time in the absence of the expansions. 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. I find the probability of Medicaid enrollment increases by 0.6–0.8 percentage points after a potentially eligible adult's birth-state expanded Medicaid. These results are in the same range of magnitudes as the baseline results, although the variables are not directly comparable.

Social connectedness is generally higher and more diverse in more urban areas, and thus there might be important differences in effect by urbanicity. Separating ZIP codes by urban and rural status I find similar effects and no evidence of heterogeneity. Social connections are also strongly related to geographic proximity. I use two strategies to explore the role of distance. First, to examine the importance of living on the border of an expansion state, I estimate the impact of expansions comparing border ZIP codes to interior ones among all states sharing a border with an expansion state. I find border ZIP codes had 1 percentage point higher scaled enrollment after the expansions compared to interior ZIP codes. Next, to assess the extent to which these border communities might drive results, I estimate regressions excluding ZIP codes within 50, 100, and 200 miles of an expansion state. I find the effect of social exposure to the Medicaid expansions remains even when only considering ZIP codes that are similarly far away from the expansion states.

Past work on network effects in public benefits participation has tended to use close geographic proximity interacted with ethnic or language groups to argue for the presence of network effects. I take a similar approach and create social network exposure variables that are specific to ethnic and language groups. Using the Social Connectedness Index, I estimate the number of, e.g., Spanish-speaking friends in expansion states that a community has per Spanish speaking residents. I find these subgroup-specific measures of social exposure impact the probability of enrollment among members of the subgroup but not others.

To further shed light on how the Medicaid experience's of one's friends might change their own knowledge and behaviors, I next turn to examine effects on individual's policy preferences. The effects of social network exposure on knowledge and preferences may not confined to just those potentially eligible for the program—having friends enrolled in Medicaid could alter policy opinions even for non-eligible adults, potentially changing public approval of the program and, in turn, influencing 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.

I estimate policy preference responses 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 using ZIP code-level SCI, I compare differences between neighborhoods within the same county and year but with differing social exposure and find similar effects. In similar analyses using alternative healthcare policy questions but without the benefit of a pre-period for comparison, 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.

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 also 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).[7]

Medicaid was established with the adoption of the Social Security Amendments of 1965,[8] 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,

[7]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/.

[8]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.

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.[9] 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.

[9] 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.

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

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

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

3 Empirical Strategy

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

3.1 Facebook Social Connectedness Index

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

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

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

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

3.2 Estimating Social Exposure Effects

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

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

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

Medicaid.

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

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

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

My treatment of interest in this case, *SocialExposure*, is a continuous measure. Recent research has highlighted the potential challenges and biases TWFE estimators with continuous measures can create (Callaway et al., 2024). 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; Callaway and Sant'Anna, 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 doublyrobust augmented inverse-probability weighting estimation procedures proposed in Callaway and Sant'Anna (2021). Their methodology decomposes the average treatment effect into a weighted average of group-time-specific treatment effects, which can then be aggregated to the average treatment effects on the treated (ATET) of interests.

3.2.1 Aggregating Social Connectedness

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

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

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

3.2.2 Sub-Population Social Connectedness

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

$SCI_{v,z}$ is a weighted average of products of the B and W population shares within each ZIP code and the between- and within-group connectedness between the ZIP codes:

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

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

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

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

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

3.2.3 Alternative Social Connectedness Proxy: Birth State

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

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

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

4 Data

4.1 American Community Survey

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

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

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

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

4.2 Cooperative Congressional Elections Study

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

4.3 California Medicaid Enrollment Counts

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

5 Results

Table 1 shows the baseline ZIP code-level results. Having one standard deviation higher strength of social connection to the Medicaid expansion states caused ZIP codes to experience a 1.5% increase in the scaled number of non-elderly adult (ages 18–64) Medicaid enrollees[10] —even though eligibility was largely unchanged in their state—compared to other ZIP codes in the same state but with less strong social connection to the expansion states. I similarly estimate the insured rate among non-elderly adults under 200% and 138% of the poverty line increased by 0.37 percentage points (0.65% of the baseline mean) and 0.58 percentage points (1.1% of the baseline mean).

To examine dynamic effects over time, assess potential pre-trends, and investigate effect heterogeniety, I next turn to the ACS microdata (Ruggles et al., 2023). Table 2 shows low-income adults in PUMAs with stronger social connections to the Medicaid expanding states were more likely to enroll in Medicaid after the expansions compared to those in PUMAs in the same state but with less connection to the expansions. Specifically, a one standard increase in friends per person in Medicaid expansion states increased the probability of take-up among potentially eligible low-income adults (parents and people with disabilities) by 0.7 percentage points.

Figure **??** [event studies]

The changes could result from people who would otherwise not have any insurance, or there could be crowd out of other sources such as employer sponsored health insurance. Figure 5 shows estimates of the impacts of PUMA social exposure to Medicaid expansions on overall insurance and individual insurance sources among potentially Medicaid eligible low-income adults. I do not find effects on insurance sources including Medicare, other public, employer sponsored, and other private, and I find a positive effect on the probability of any insurance coverage that is similar in magnitude to the effect on Medicaid. This evidence is suggestive that the effects are drive by individuals gaining new coverage rather than switching coverage sources.

Figure A5 [CA results]

[10]ZIP code data from the American Community Survey is published as 5-year pooled estimates. I use data from the 2008-12, 2009-13, 2014-18, and 2015-19 periods. Since Medicaid enrollment is only published as ZIP code population counts for selected age groups, I scale Medicaid enrollment by the under 200% poverty line population rather than a take-up rate. The ACS does publish rates of any insurance for selected age groups and income levels, which I use as additional outcomes.

A final validity concern is the possibility that contemporaneous, correlated shocks could occur even at the ZIP code level. As another robustness check, I next consider a different proxy for one's social network: their 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 individuals living within the same PUMA but born in different states. The identifying assumption is that individuals living within the same PUMA would have the same evolution of Medicaid take-up over time in the absence of the expansions. 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. The probability of Medicaid enrollment increases by 0.6–0.8 percentage points after a potentially eligible adult's birth-state expanded Medicaid (Table 5). These results are in the same range of magnitudes as the baseline results, although the variables are not directly comparable.

Social connectedness is generally higher and more diverse in more urban areas, and thus there might be important differences in effect by urbanicity. Separating ZIP codes by urban and rural status I find similar effects and no evidence of heterogeneity (Table 3). Social connections are also strongly related to geographic proximity. I use two strategies to explore the role of distance. First, to examine the importance of living on the border of an expansion state, I estimate the impact of expansions comparing border ZIP codes to interior ones among all states sharing a border with an expansion state. I find border ZIP codes had 1 percentage point higher scaled enrollment after the expansions compared to interior ZIP codes (Table 4). Next, to assess the extent to which these border communities might drive results, I estimate regressions excluding ZIP codes within 50, 100, and 200 miles of an expansion state. I find the effect of social exposure to the Medicaid expansions remains even when only considering ZIP codes that are similarly far away from the expansion states.

Past work on network effects in public benefits participation has tended to use close geographic proximity interacted with ethnic or language groups to argue for the presence of network effects. I take a similar approach and create social network exposure variables that are specific to ethnic and language groups. Using the Social Connectedness Index, I estimate the number of, e.g., Spanish-speaking friends in expansion states that a community has per Spanish speaking residents. I find these subgroup-specific measures of social exposure impact the probability of enrollment among members of the subgroup but not others.

To further shed light on how the Medicaid experience's of one's friends might change their own knowledge and behaviors, I next turn to examine effects on individual's policy preferences. The effects of social network exposure on knowledge and preferences may not confined to just those potentially eligible for the program—having friends enrolled in Medicaid could alter policy opinions even for non-eligible adults, potentially changing public approval of the program and, in turn, influencing 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.

I estimate policy preference responses 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 using ZIP code-level SCI, I compare differences between neighborhoods within the same county and year but with differing social exposure and find similar effects. In similar analyses using alternative healthcare policy questions but without the benefit of a pre-period for comparison, 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.

6 Conclusion

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 also 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.

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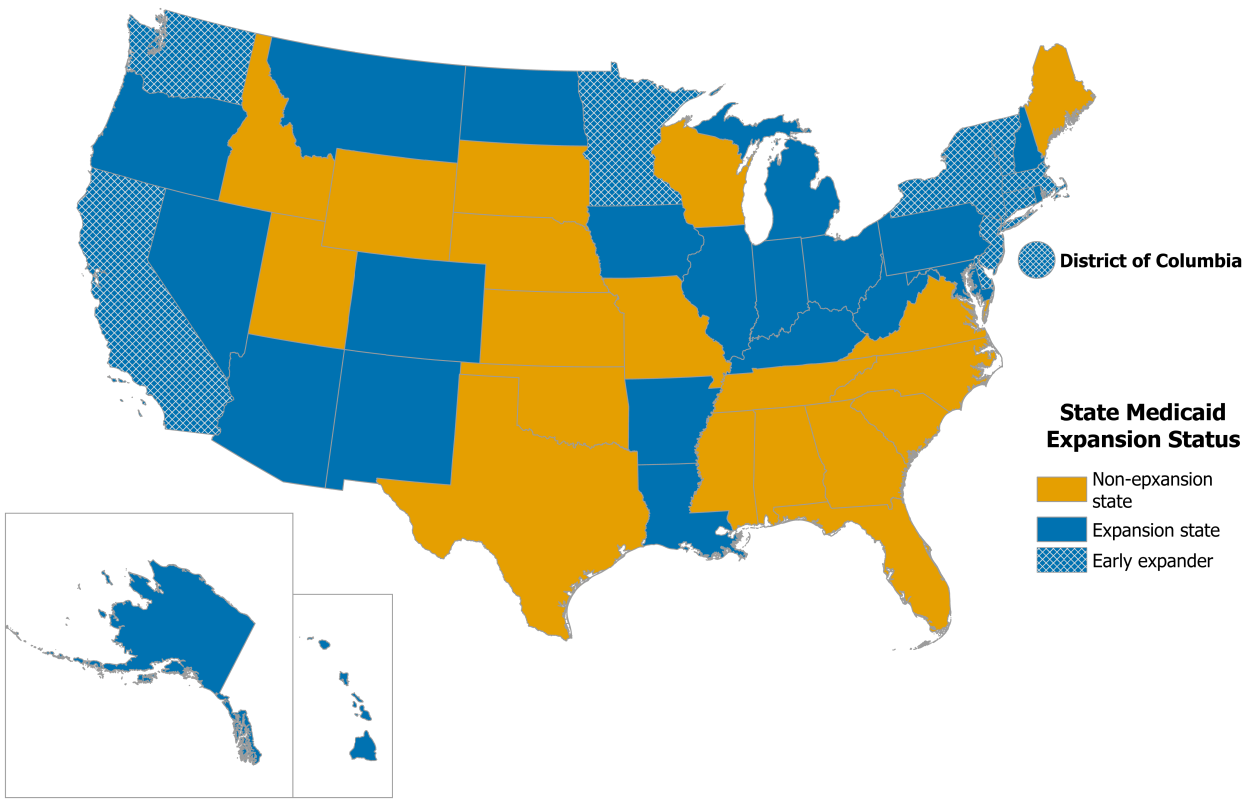
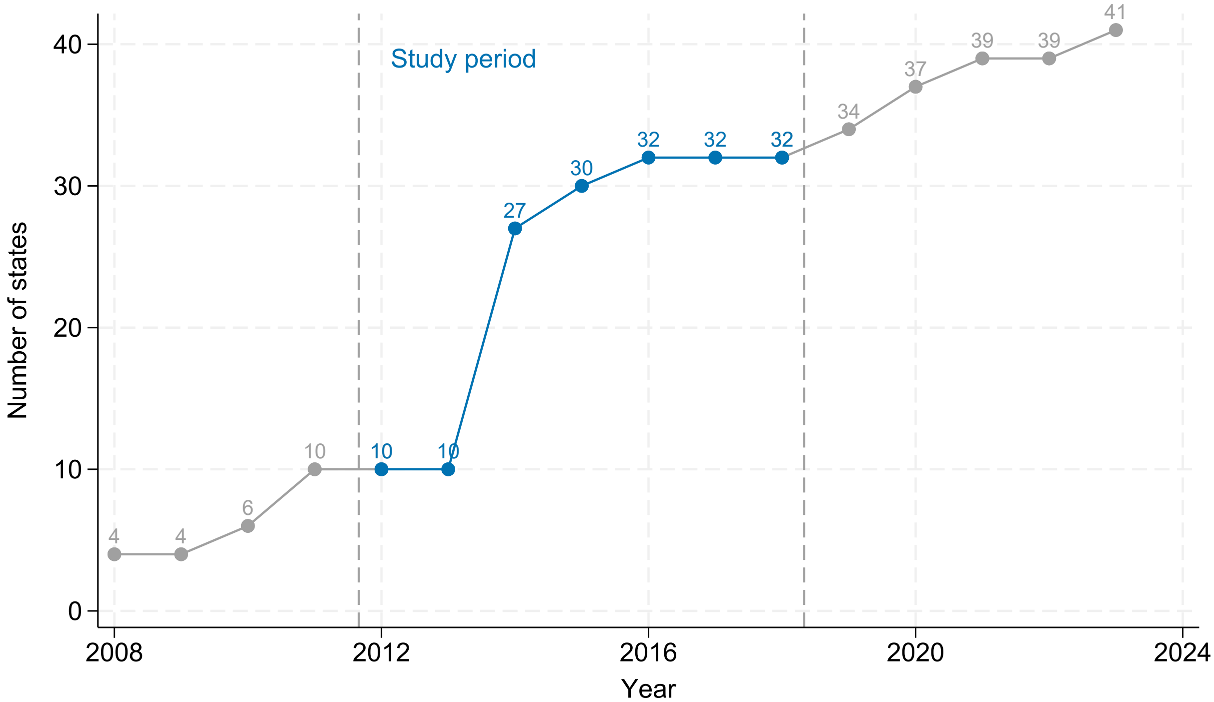
7 Figures

Figure 1: States' ACA Medicaid expansion status in 2018



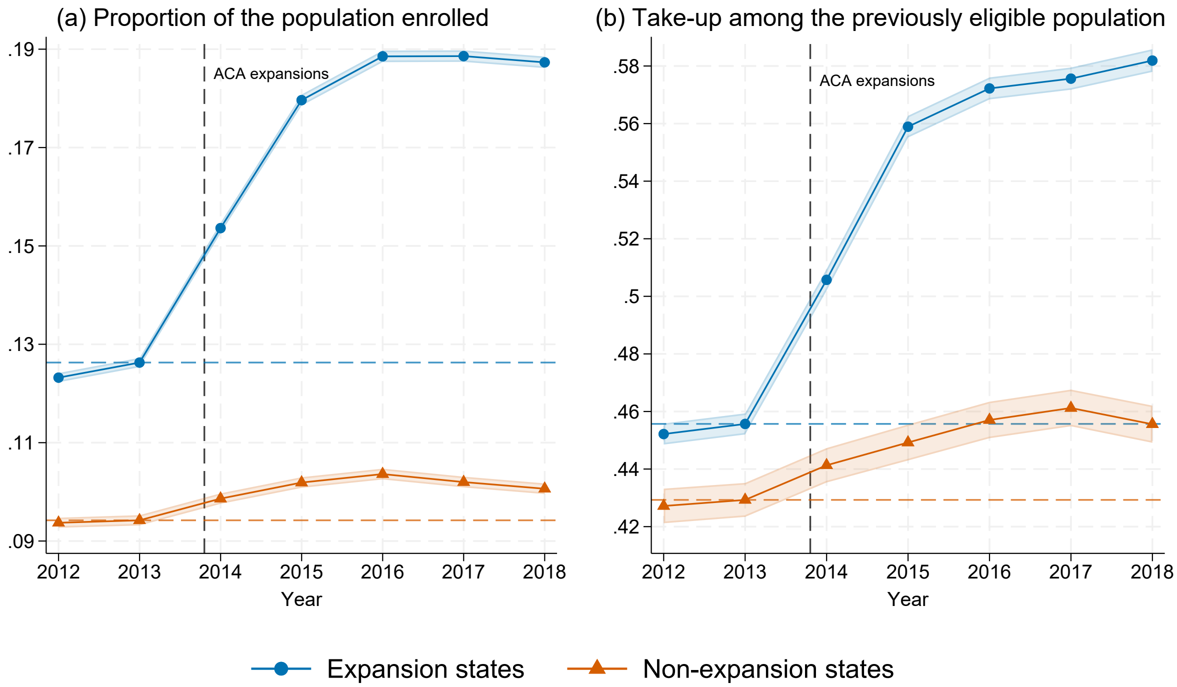
Notes: This map shows states' Medicaid expansion status—extending eligibility to all low-income (<138% poverty) adults under the Affordable Care Act (ACA)—as of 2018. States with Medicaid programs that covered all low-income adults before the 2014 ACA expansions are defined as already expanded. Data come from the Kaiser Family Foundation (Kaiser Family Foundation, 2023) and are supplemented with additional state information. Five states (California, Connecticut, Minnesota, New Jersey, Washington) and the District of Columbia implemented early expansions in 2010–2011. California implemented a staggered adoption across counties during 2011–2012. The early expansions in New Jersey and Washington did not add new enrollment (Sommers et al., 2013) and so they are defined as 2014 expanders in the main analyses. Four states already had Medicaid programs that broadly covered low-income adults before passage of the ACA and are included as early expanders: Delaware since 1996, Massachusetts since 2006, New York since 2001, and Vermont since 2000. Nine states expanded Medicaid between 2019 and 2023: Maine and Virginia in 2019; Idaho, Nebraska, and Utah in 2020; Missouri and Oklahoma in 2021; and North Carolina and South Dakota in 2023.

Figure 2: Trend in number of states with expanded Medicaid



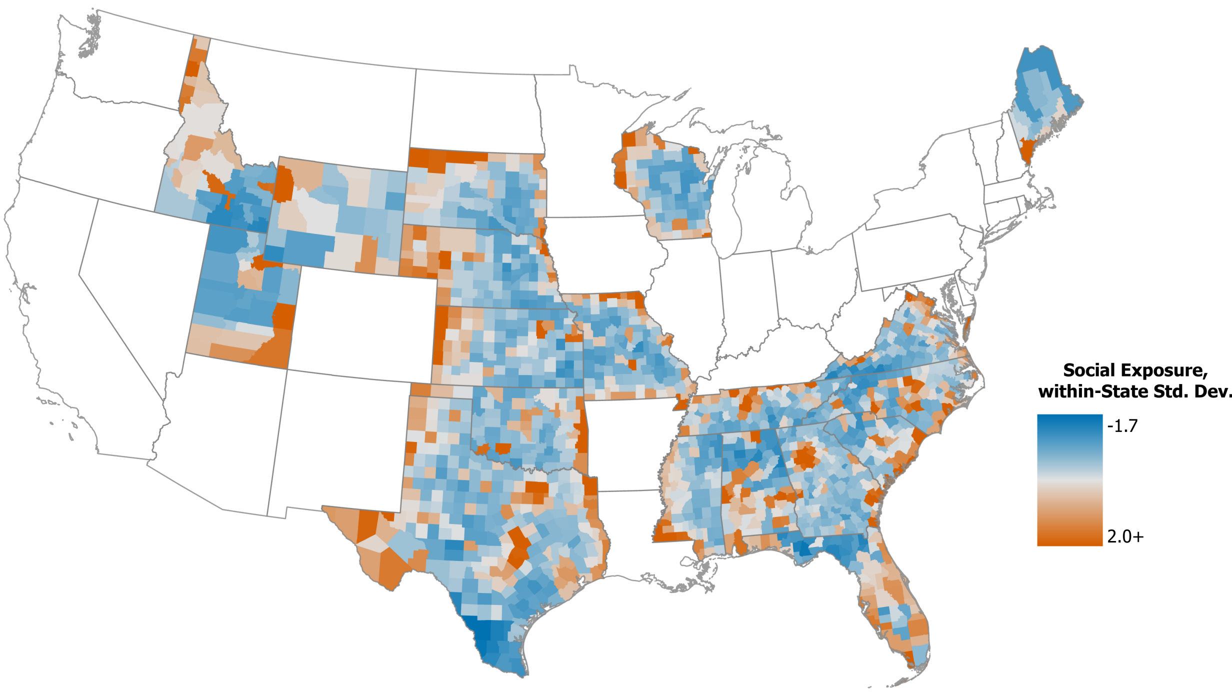
Notes: This figure shows the trend in the number of states that had expanded Medicaid to cover all low-income adults. Pre-ACA and early expansion states are described in the notes to Figure 1. Dashed lines delineate the beginning and end of the study period.

Figure 3: Medicaid enrollment trends among adults ages 18–64



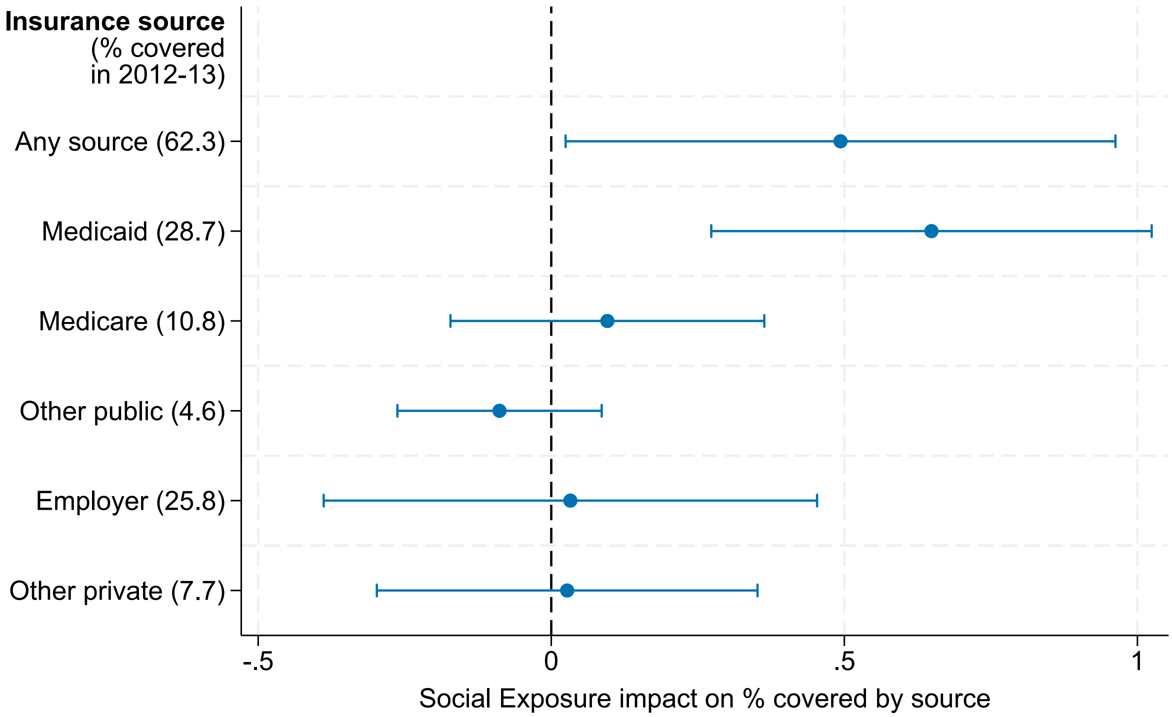
Notes: This figure shows trends in (a) the proportion of all adults ages 18–64 enrolled in Medicaid; and (b) the proportion of previously eligible adults enrolled in Medicaid. Previously eligible defined based on 2013 eligibility thresholds according to Kaiser Family Foundation data. Proportions estimated using American Community Survey (ACS) annual person-level weights, with 95% confidence intervals adjusted for the ACS complex sample design.

Figure 4: Within-state variation in county-level social connectedness to Medicaid expansion states



Notes: County social connectedness to Medicaid expansion states, standardized within each state. ZIP code-level and PUMA level Social Exposure maps shown in Figure A2 and Figure A3, respectively.

Figure 5: Social Exposure impact on health insurance coverage by source, potentially eligible adults ages 18–64 in non-expansion states, 2012–2018



Notes:

8 Tables

Table 1: Effect of Social Exposure to Medicaid expansions on local adult Medicaid enrollment, ZIP codes in non-expansion states in 2010–2011 and 2016–2017

	Medicaid	Insured rate (%), by income:	
	Scaled enrollment (%)	<200% pov.	<138% pov.
	(1)	(2)	(3)
Social Exposure	0.390***	0.373***	0.577***
	(0.120)	(0.127)	(0.147)
ZIP code fixed effects	Y	Y	Y
State × year fixed effects	Y	Y	Y
ZIP code controls	Y	Y	Y
Outcome mean at baseline	25.841	57.505	54.271
ZIP codes	8,691	8,671	8,664
ZIP code-year observations	34,764	34,647	34,580

Notes: * $p < .10$, ** $p < .05$, *** $p < .01$. Standard errors (in parentheses) clustered at the ZIP code level. Social Exposure is standardized as the z-score and therefore results should be interpreted as the effect of a one standard deviation increase in Social Exposure. Each ZIP code-year observation is based on American Community Survey (ACS) 5-year pooled estimates, accessed through IPUMS NHGIS (Manson et al., 2023). Log(enrollment) is the natural logarithm of the total number of adults ages 18–64 enrolled in Medicaid living in the ZIP code. Scaled enrollment is the total enrollment divided by the number of adults ages 18–64 with income under 200% of the poverty line, multiplied by 100. Insured rate is the ACS estimated percent of adults ages 18–64 with incomes under 200% and 138% of the poverty line who have any health insurance coverage.

Table 2: Effect of Social Exposure to Medicaid expansions on probability of Medicaid enrollment, low-income adults ages 18–64 in non-expansion states, 2012–2018

	P(Medicaid enrolled) among:		
	All adults	Potential eligibles	Non-eligibles
	(1)	(2)	(3)
Social Exposure	0.0037**	0.0065***	0.0013
	(0.0016)	(0.0023)	(0.0019)
PUMA fixed effects	Y	Y	Y
State-year fixed effects	Y	Y	Y
Individual controls	Y	Y	Y
Outcome mean in 2012-13	0.1860	0.2829	0.0923
Number of PUMAs	911	911	911
Number of observations	2,035,629	967,285	1,068,344

Notes: * $p < .10$, ** $p < .05$, *** $p < .01$. Standard errors (in parentheses) clustered at the PUMA level. Social Exposure is standardized as the z-score and therefore results should be interpreted as the effect of a one standard deviation increase in Social Exposure. Sample includes adults ages 18–64 with family income below 200% of the Federal Poverty Guideline (FPG). Potential eligibles includes parents and people reporting a disability; non-eligibles are childless adults not reporting a disability. Income controls includes state specific controls for family income as a percent of the FPG.

Table 3: Heterogeneity in Social Exposure impact on Medicaid enrollment by rural status, ZIP codes in non-expansion states in 2010–2011 and 2016–2017

	Scaled Medicaid enrollment, among:		
	All	Rural	Urban
	(1)	(2)	(3)
Social Exposure	0.388***	0.521**	0.375**
	(0.119)	(0.233)	(0.162)
Rural × Social Exposure	−0.021		
	(0.138)		
ZIP code fixed effects	Y	Y	Y
State × year fixed effects	Y	Y	Y
ZIP code controls	Y	Y	Y
Outcome mean at baseline	25.841	30.434	23.901
ZIP codes	8,691	5,434	3,257
ZIP code-year observations	34,764	21,736	13,028

Notes: * $p < .10$, ** $p < .05$, *** $p < .01$. Standard errors (in parentheses) clustered at the ZIP code level. Social Exposure is standardized as the z-score and therefore results should be interpreted as the effect of a one standard deviation increase in Social Exposure. Each ZIP code-year observation is based on American Community Survey (ACS) 5-year pooled estimates, accessed through IPUMS NHGIS (Manson et al., 2023). Scaled enrollment is the total enrollment divided by the number of adults ages 18–64 with income under 200% of the poverty line, multiplied by 100.

Table 4: The role of distance in social exposure effects, age 18–64 Medicaid enrollment in non-expansion ZIP codes

	Effect on scaled Medicaid enrollment by ZIP codes distance to nearest expansion state:			
	>50 miles	>100 miles	>200 miles	Border states
	(1)	(2)	(3)	(4)
Social Exposure	0.429***	0.399**	0.403*	
	(0.159)	(0.162)	(0.231)	
Border ZIP				1.022**
				(0.399)
ZIP codes	6,818	5,169	2,365	5,606
ZIP code-time observations	27,272	20,676	9,460	22,424

Notes: * $p < .10$, ** $p < .05$, *** $p < .01$. Standard errors (in parentheses) clustered at the ZIP code level. Each column includes only ZIP codes within the given distance restriction to the nearest Medicaid expansion state (e.g., column (1) includes only ZIP codes at least 50 miles away from an expansion state). Border states excludes the five states that do not share a border with an expansion state (Alabama, Florida, Georgia, North Carolina, South Carolina). Social Exposure is standardized as the z-score with respect to the total sample of non-expansion state ZIP codes in 2016. Border ZIP defined as bottom quartile of distance to an expansion state, among border states (<38 miles). Each ZIP code-year observation is based on American Community Survey (ACS) 5-year pooled estimates.

Table 5: Effect of birth state expanding Medicaid on own probability of Medicaid enrollment, low-income adults ages 18–64 in non-expansion states, 2012–2018

	Probability enrolled in Medicaid	
	(1)	(2)
Birth state expanded Medicaid	0.0063**	0.0083**
	(0.0028)	(0.0034)
Individual controls	Y	Y
PUMA-treatment group fixed effects	Y	Y
PUMA-year fixed effects	Y	Y
Restrict to those born in other U.S. state		Y
Outcome mean in 2012-13	0.2872	0.2331
Number of PUMAs	911	911
Number of observations	967,285	282,028

Notes: * $p < .10$, ** $p < .05$, *** $p < .01$. Standard errors (in parentheses) clustered at the PUMA level. Sample includes adults ages 18–64 with family income below 200% of the Federal Poverty Guideline (FPG). Individual controls include state specific controls for family income as a percent of the FPG and an indicator for whether the individual moved into the state in the past year. Treatment groups include (1) born in-state, (2) born out-of-state in a non-expansion state, (3) born outside the U.S., (4) born in an early expansion state, (5) born in a 2014 expansion state, (6) born in a 2015 expansion state, and (7) born in a 2016 expansion state.

Table 6: 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 7: 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.

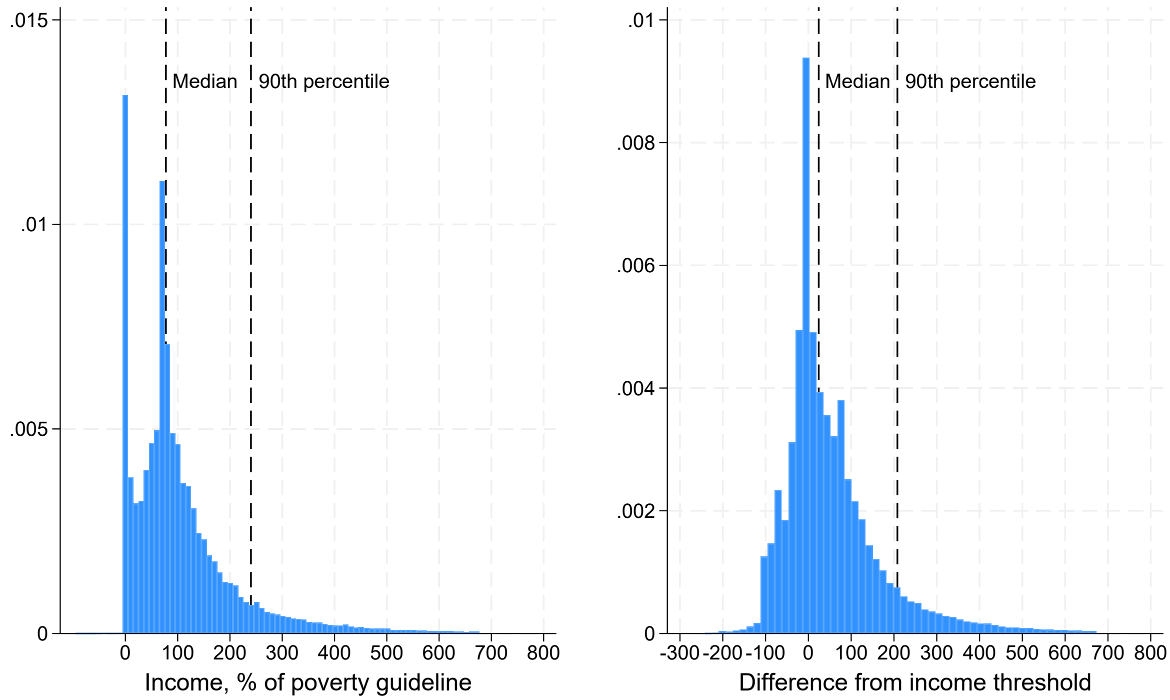
A Supplemental Exhibits

Table A1: Summary characteristics of ACS respondents ages 18–64 and covered by Medicaid

	Non-expansion states		Expansion states	
	2012-2013	2017-2018	2012-2013	2017-2018
Male	0.41	0.42	0.42	0.45
Age				
18-25	0.22	0.21	0.22	0.21
26-44	0.40	0.40	0.41	0.42
45-64	0.38	0.39	0.37	0.37
Race/ethnicity				
NH-white	0.51	0.49	0.47	0.46
NH-Black	0.29	0.28	0.20	0.17
Hispanic	0.16	0.17	0.23	0.26
NH-other	0.05	0.06	0.10	0.11
Educational attainment				
Less than high school	0.26	0.22	0.24	0.19
High school	0.48	0.49	0.46	0.47
Some college	0.20	0.21	0.22	0.23
BA or more	0.06	0.08	0.08	0.11
Employment status				
Employed	0.28	0.34	0.34	0.45
Unemployed	0.11	0.07	0.13	0.09
Not in labor force	0.61	0.59	0.53	0.46
Family income, % of FPG	109	122	112	134
Parent	0.46	0.43	0.48	0.42
Disabled	0.40	0.38	0.33	0.26
Childless, non-disabled adult	0.26	0.29	0.29	0.39
Medicaid eligible (strict)	0.36	0.30	0.49	0.65

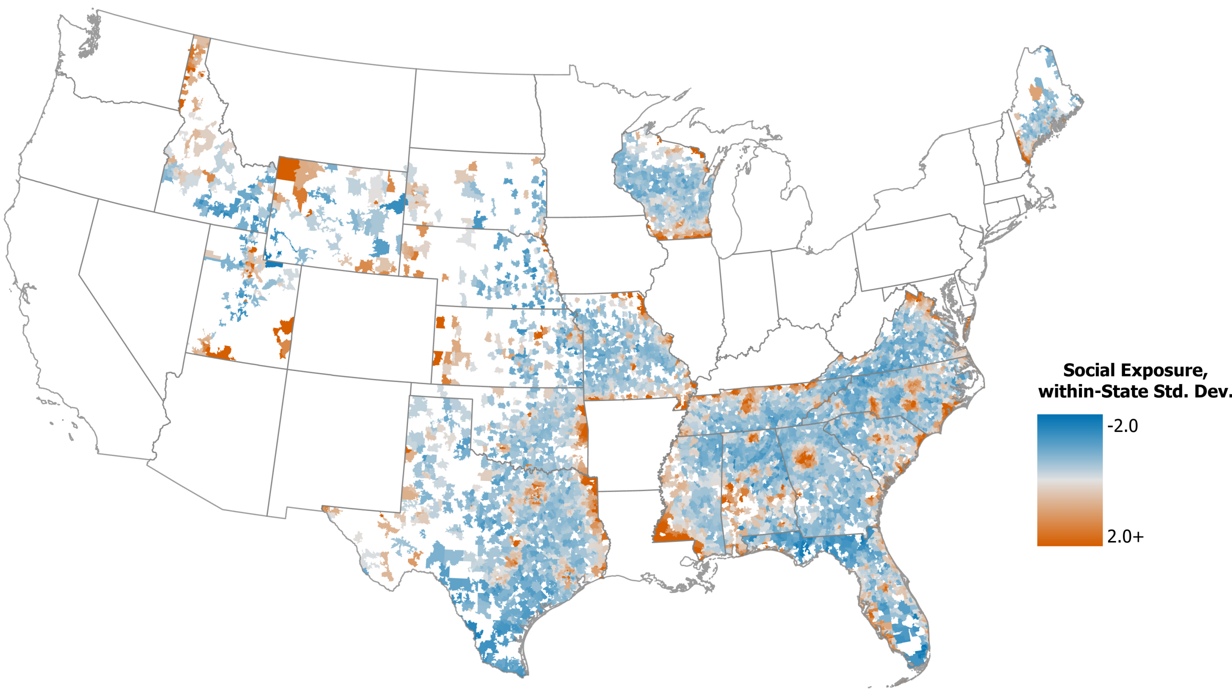
Notes: NH, Non-Hispanic; BA, Bachelor's Degree; FPG, Federal Poverty Guideline. Statistics are proportions unless otherwise noted. Statistics weighted using American Community Survey person-level weights. Expansion and Non-expansion states defined in Figure 1 Family income defined at the health insurance unit level.

Figure A1: Distribution of reported income among ACS respondents reporting Medicaid coverage, adults ages 18–64 living in non-expansion states in 2012–2018



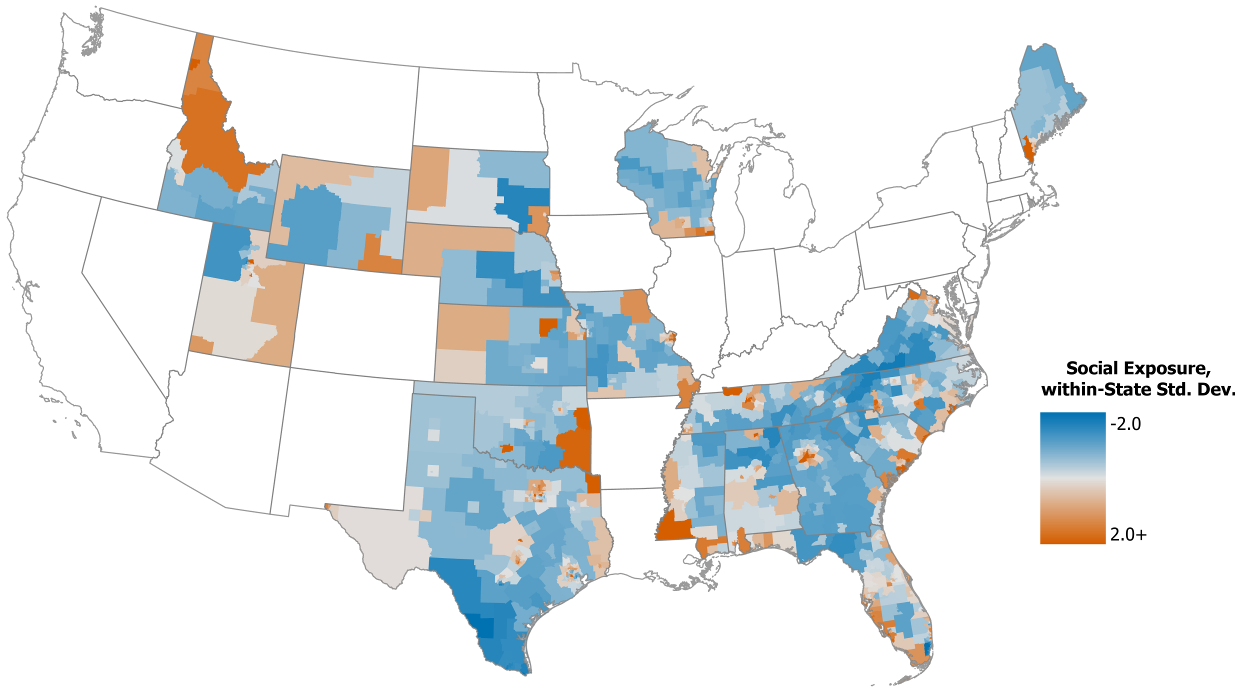
Notes:

Figure A2: Within-State variation in ZIP code-level Social Exposure to Medicaid expansion states



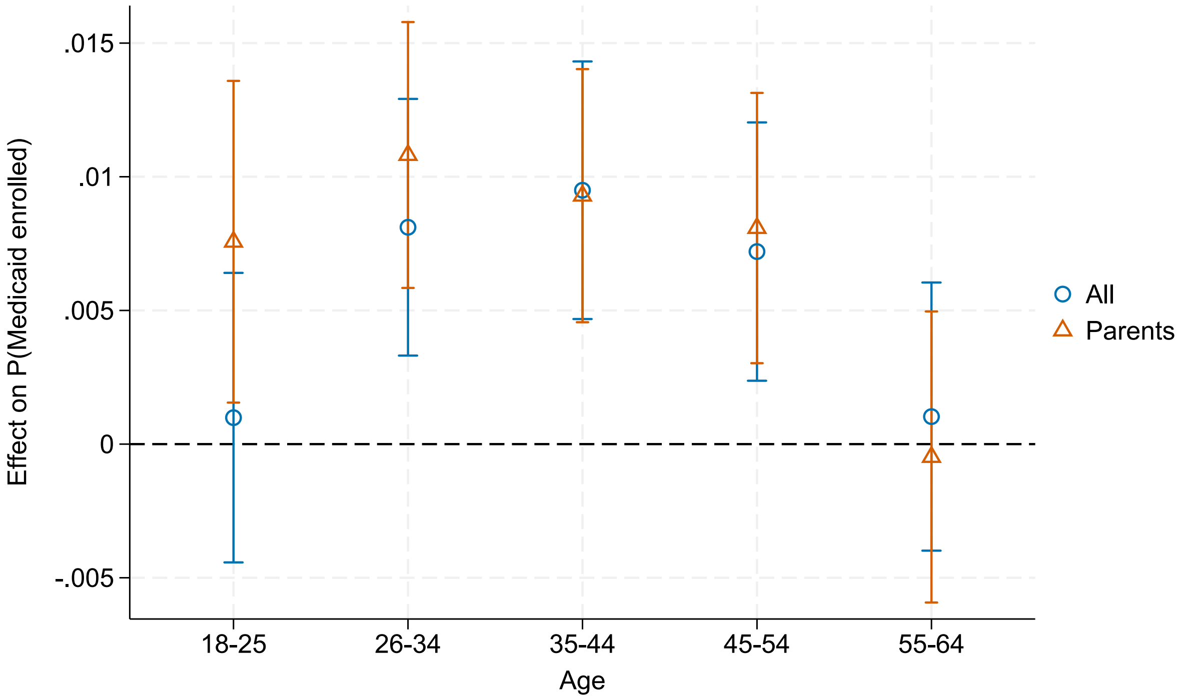
Notes:

Figure A3: Within-State variation in PUMA-level Social Exposure to Medicaid expansion states



Notes:

Figure A4: Effect of Social Exposure on probability of Medicaid enrollment, low-income adults ages 18–64 living in non-expansion states in 2012–2018



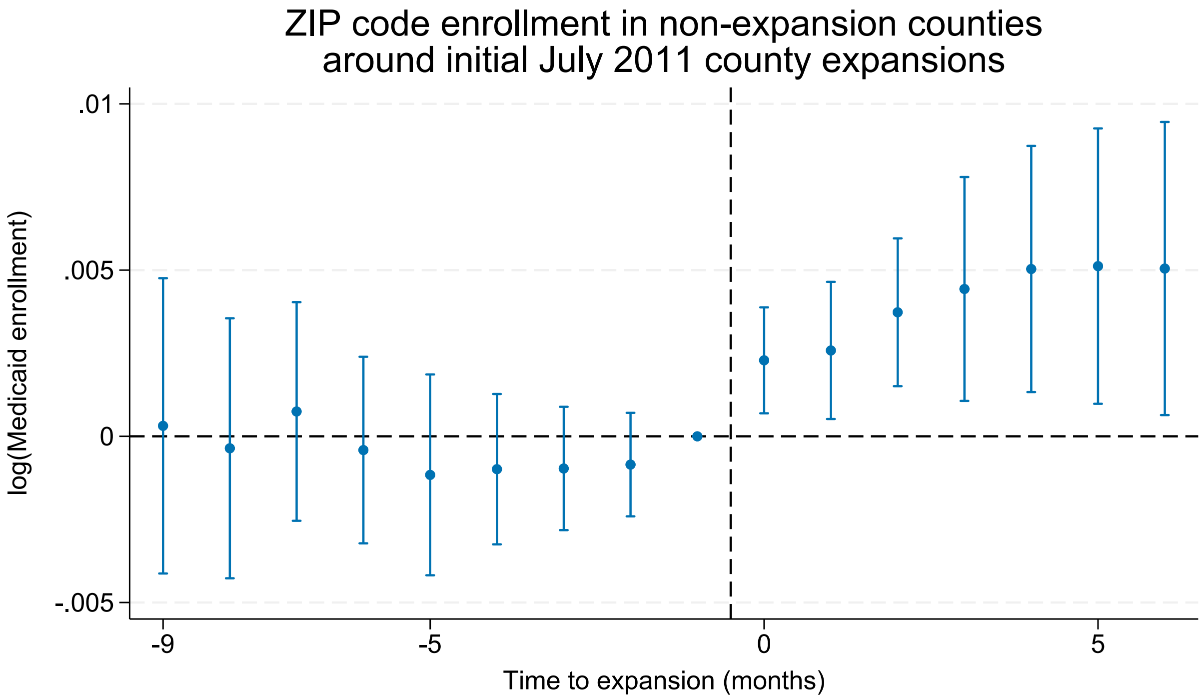
Notes:

Table A2: Effect of Social Exposure to Medicaid expansions on probability of Medicaid enrollment, low-income population in non-expansion states, 2012–2018

	P(Medicaid enrolled) among:			
	All	Ages <18	Ages 18-64	Ages 65+
Social exposure	0.005***	0.003	0.005***	0.002
	(0.002)	(0.004)	(0.002)	(0.003)
PUMA fixed effects	Y	Y	Y	Y
State-year fixed effects	Y	Y	Y	Y
Income controls	Y	Y	Y	Y
Outcome mean, 2012-13	0.348	0.665	0.206	0.245
Number of observations	3,084,270	802,678	1,724,350	557,242

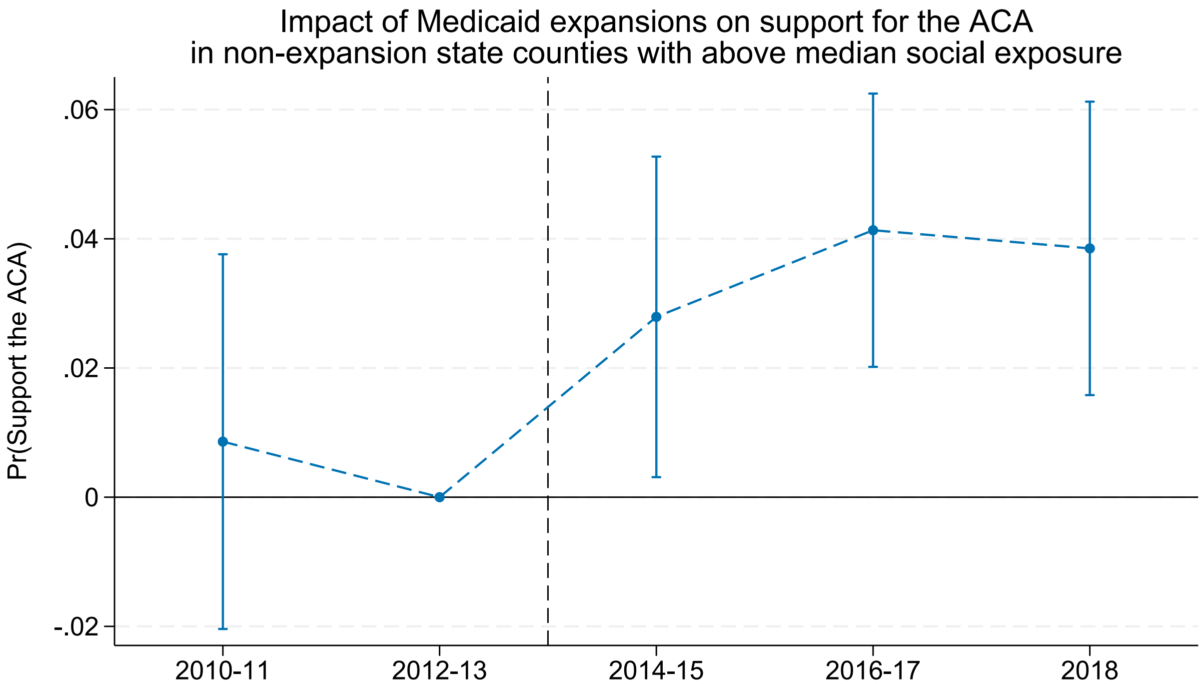
Notes: * $p < .10$, ** $p < .05$, *** $p < .01$. Standard errors (in parentheses) clustered at the PUMA level. Social Exposure is standardized as the z-score and therefore results should be interpreted as the effect of a one standard deviation increase in Social Exposure. Sample includes respondents of all ages with family income below 200% of the Federal Poverty Guideline (FPG).

Figure A5: Event study for impact of above-median social exposure to California county Medicaid expansions on ZIP code-level enrollment



Notes:

Figure A6: Impact of above median social exposure to Medicaid expansions on county-level approval of the ACA



Notes:

Table A3: 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