

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

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## Abstract

Understanding the influence of individuals' social networks on their interactions with public programs is important for evaluating program outcomes and shaping future policy. In contexts where social frictions, such as incomplete information and stigma, are prevalent, policy changes might cause unanticipated indirect impacts operating through social channels. This paper studies social spillover effects arising from changes in program eligibility criteria and how they impact the previously- and non-eligible populations not targeted by the policy change. I focus on state-level changes to Medicaid, the United States' low-income public health insurance program, during the 2010s. Using the Facebook Social Connectedness Index to capture network connections across ZIP codes, I isolate social spillover effects by estimating the impacts out-of-state eligibility expansions had on interactions with Medicaid in socially connected communities within non-expansion states. Areas with 1 standard deviation stronger social ties to states expanding Medicaid eligibility experienced 1-2pp increases in program take-up following the policy change, even though eligibility was unaffected in their own state. The increase in Medicaid was reflected in decreases in uninsurance rates, suggesting the effect was driven by people becoming newly insured. I similarly find areas with stronger social connections to the expansions exhibited increased public support for Medicaid and the Affordable Care Act, and this effect was driven by higher income individuals who would not directly benefit from the program. I explore the roles of information

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and stigma as potential channels of effect. The results highlight the potential indirect social impacts policy changes can have and underscore the policy consequences of our increasing social connectedness across geographic space.

# 1 Introduction

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

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

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

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

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

I first estimate effects on Medicaid take-up using American Community Survey data. I find that potentially eligible non-elderly adults in Public Use Microdata Areas (PUMAs) with one standard deviation more friends per person in Medicaid expansion states were 1.3 percentage points more likely to be enrolled in Medicaid after the 2014 ACA expansions—

even though eligibility was largely unchanged for themselves. The impact on Medicaid enrollment was reflected in the uninsured rate (1.6 percentage point decrease) while the probability of being covered by other sources did not change, suggesting the results are driven by otherwise uninsured individuals becoming Medicaid covered. The effects translate to an overall Medicaid take-up rate in non-expansion states that was 1.6 percentage point higher in 2018 than it would have otherwise been without the presence of social spillovers from the expansions, resulting in about 110,000 more individuals covered by Medicaid in 2018.

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

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

In a cross-sectional analysis I estimate the effects of changes in a ZIP codes number of friends per person exposed to Medicaid expansions. I find ZIP codes with one standard deviation higher social exposure were more likely to support their own state expanding

Medicaid (4.6 percentage point increase) and increasing healthcare spending (2.2 percentage point increase), whereas I do not find a statistically significant difference in preferences for welfare spending. These results suggest the effects are driven by specifically healthcare related policy preferences.

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

Finally, to further explore potential mechanisms of effect on both take-up and preferences, I utilize polling data from the Kaiser Family Foundations monthly Health Tracking Poll [NOTE: data approved, add in next draft]

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

## 1.1 Related Literature

The results contribute to a few strands of literature. First, I build on the literature on incomplete public benefits take-up and related barriers ([Ko and Moffitt, 2022](#); [Janssens and Van Mechelen, 2022](#); [Moffitt, 1983](#); [Heckman and Smith, 2004](#); [Bhargava and Manoli, 2015](#); [Aizer, 2003](#)), in particular the role of social spillovers in program take-up ([Bertrand et al., 2000](#); [Aizer and Currie, 2004](#); [Dahl et al., 2014b,a](#)). Experimental evidence has found that

interventions providing program information to potential beneficiaries can improve take-up ([Bhargava and Manoli, 2015](#); [Finkelstein and Notowidigdo, 2019](#)). Social networks might help provide additional program information; most evidence focuses on very local social ties (e.g., neighbors), examining associations between individuals' own program behavior and the behavior of their local network ([Bertrand et al., 2000](#); [Aizer and Currie, 2004](#); [Chetty et al., 2013](#); [Grossman and Khalil, 2020](#)). It can be difficult to distinguish social network effects in this approach from other explanations such as endogenous sorting into neighborhoods or the effects of other correlated neighborhood characteristics. By examining the effects of a distant policy change that did not directly impact the study population, I isolate the social network impacts from these other potential explanations. Focusing on hyper-local networks also misses the growing importance of distant networks facilitated by communication technology, which are nearly as important but might operate differently from the impacts of local networks. I contribute to the limited evidence examining the effects of broader social networks ([Dahl et al., 2014b](#); [Wilson, 2022](#)).

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

A smaller literature related to program take-up has studied so-called “woodwork effects,” where previously eligible individuals are induced to enroll in a program after eligibility expansions. Most of this evidence comes from Medicaid expansions ([Frean et al., 2017](#); [Sonier et al., 2013](#); [Sacarny et al., 2022](#); [Hudson and Moriya, 2017](#); [Sommers et al., 2012](#)). These studies tend to estimate the effects of a state expanding eligibility for a program on the behavior of the previously eligible in the same state ([Anders and Rafkin, 2022](#)). Researchers theorize this “woodwork effect” is driven by a combination of social network effects improving information or stigma frictions, but it is challenging to disentangle these social effects from other program changes that might otherwise reduce transaction costs for the previously eligible (e.g., through accompanying program operation changes), and more work is needed in this area ([Sacarny et al., 2022](#)). Since individuals in my study population are not directly impacted by the policy change, I argue my results are exclusively caused

by social network effects, providing evidence that social networks add a distinct take-up effect independent from other program changes. Moreover, this evidence tends to come from estimating the impacts of having a parent become eligible for Medicaid on their previously eligible child’s enrollment—I instead focus on adult peer networks, which might operate very differently than the effects of within-household eligibility changes. Finally, scant evidence has examined the apparent woodwork effect that occurred in the non-expansion states, and those that do touch on this subject come to conflicting findings on whether a woodwork effect occurred in the non-expansion states (Frean et al., 2017; Courtemanche et al., 2017). I fill this gap by providing evidence that a woodwork effect occurred in the non-expansion states, operating through social ties to the expansion states.

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

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

Finally, my work contributes to a growing literature on the impacts of geographically distant social networks more generally, particularly for financial decisions (Kuchler and Stroebel,

2021). For example, [Hu \(2022\)](#) estimates the impact of being socially connected to distant flood events and finds it increases flood insurance purchases. And [Bailey et al. \(2018b\)](#) and [Bailey et al. \(2019\)](#) find changes in geographically distant housing markets impact people's house price expectations and purchasing decisions. I extend this work to include public program take-up and public approval as an economic behavior that can be influenced through social networks.

## References

- Aizer, Anna**, “Low Take-Up in Medicaid: Does Outreach Matter and for Whom?,” *American Economic Review*, May 2003, 93 (2), 238–241.
- , “Public Health Insurance, Program Take-Up, and Child Health,” *The Review of Economics and Statistics*, August 2007, 89 (3), 400–415.
- and **Janet Currie**, “Networks or Neighborhoods? Correlations in the Use of Publicly-Funded Maternity Care in California,” *Journal of Public Economics*, December 2004, 88 (12), 2573–2585.
- Anders, Jenna and Charlie Rafkin**, “The Welfare Effects of Eligibility Expansions: Theory and Evidence from SNAP,” 2022.
- Baicker, Katherine, William J. Congdon, and Sendhil Mullainathan**, “Health Insurance Coverage and Take-Up: Lessons from Behavioral Economics,” *The Milbank Quarterly*, 2012, 90 (1), 107–134.
- Bailey, Michael, Abhinav Gupta, Sebastian Hillenbrand, Theresa Kuchler, Robert Richmond, and Johannes Stroebel**, “International Trade and Social Connectedness,” *Journal of International Economics*, March 2021, 129, 103418.
- , **Eduardo Dávila, Theresa Kuchler, and Johannes Stroebel**, “House Price Beliefs And Mortgage Leverage Choice,” *The Review of Economic Studies*, November 2019, 86 (6), 2403–2452.
- , **Rachel Cao, Theresa Kuchler, Johannes Stroebel, and Arlene Wong**, “Social Connectedness: Measurement, Determinants, and Effects,” *Journal of Economic Perspectives*, June 2018, 32 (3), 259–80.
- , **Ruiqing Cao, Theresa Kuchler, and Johannes Stroebel**, “The Economic Effects of Social Networks: Evidence from the Housing Market,” *Journal of Political Economy*, December 2018, 126 (6), 2224–2276.
- Bansak, Cynthia and Steven Raphael**, “The Effects of State Policy Design Features on Take-up and Crowd-out Rates for the State Children’s Health Insurance Program,” *Journal of Policy Analysis and Management*, 2007, 26 (1), 149–175.
- Bertrand, Marianne, Erzo F P Luttmer, and Sendhil Mullainathan**, “Network Effects and Welfare Cultures,” *Quarterly Journal of Economics*, 2000, 115 (3).

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

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

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

— , **Andrew Goodman-Bacon, and Pedro H. C. Sant’Anna**, “Difference-in-Differences with a Continuous Treatment,” July 2021.

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

**Kaiser Family Foundation**, “Medicaid’s Role in Nursing Home Care,” 2017.

— , “Status of State Medicaid Expansion Decisions,” <https://www.kff.org/medicaid/issue-brief/status-of-state-medicaid-expansion-decisions-interactive-map/> 2023.

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

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

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

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

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

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

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

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

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

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

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

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

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

**Shigeoka, Hitoshi and Yasutora Watanabe**, “Policy Diffusion Through Elections,” July 2023.

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

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

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

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

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

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

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

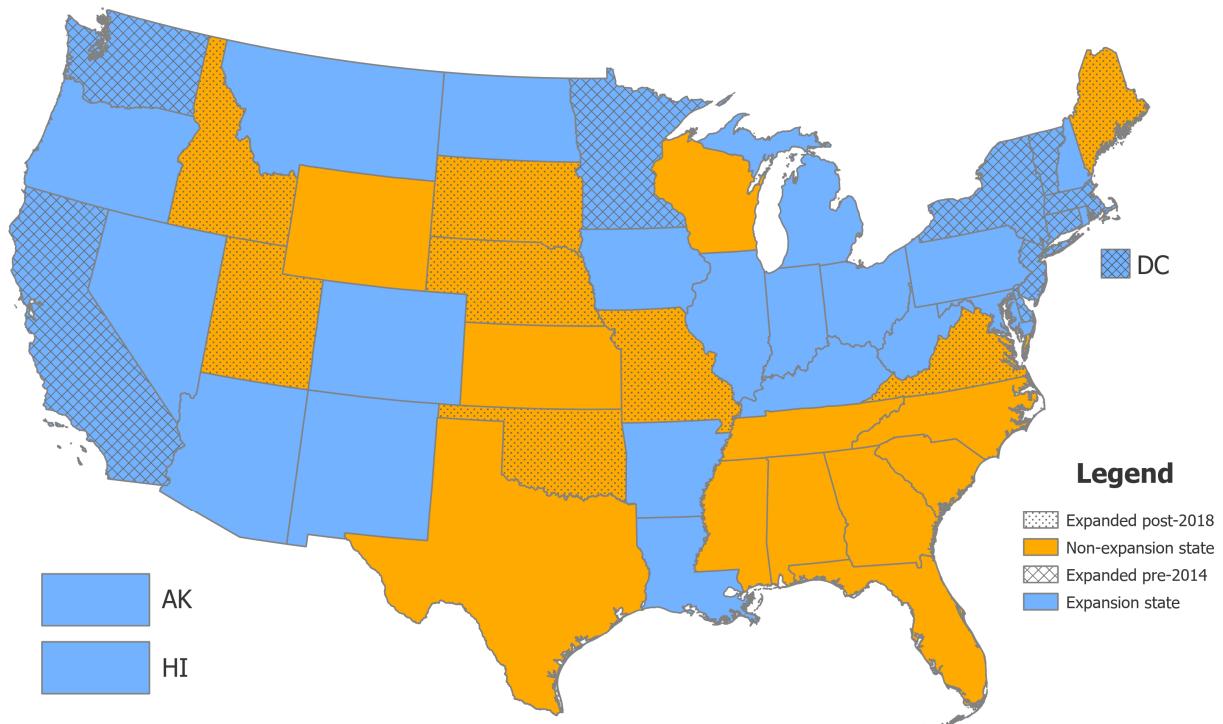
**Walker, Jack L.**, “The Diffusion of Innovations among the American States,” *American Political Science Review*, 1969, 63 (3), 880–899.

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

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

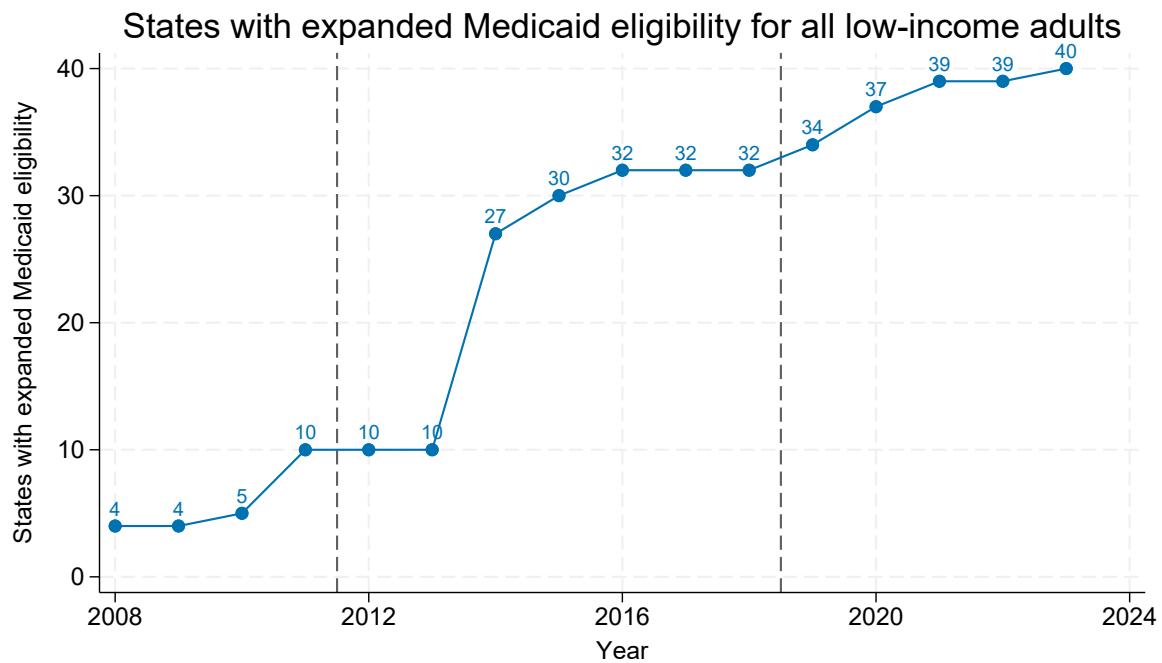
## 2 Figures

Figure 1: States' ACA Medicaid expansion status in 2018



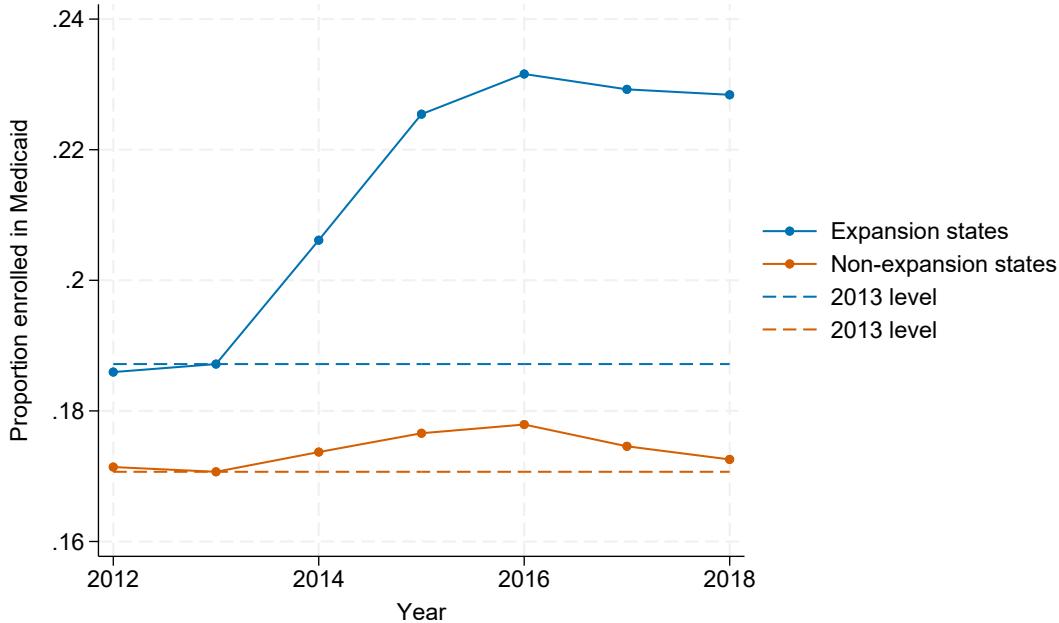
Notes: This map shows states' Medicaid expansion status—extending eligibility to all low-income ( $<138\%$  poverty) adults—as of 2018. States with Medicaid programs that covered all low-income adults before the 2014 ACA expansions are defined as already expanded. Data come from the Kaiser Family Foundation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

Figure 2: State ACA Medicaid expansions trend, 2008–2023

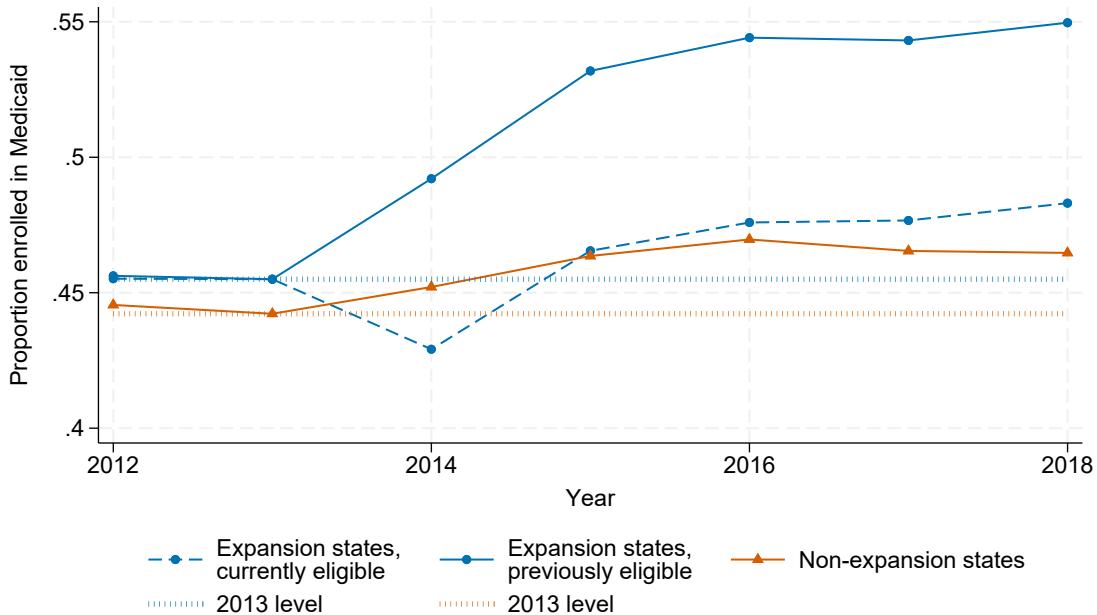


Notes: This figure shows the trend in the number of states that had expanded Medicaid to cover all low-income (<138% poverty) adults. States with Medicaid programs that covered all low-income adults before the ACA expansions are defined as expanded; early expanding states are described in the notes to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

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



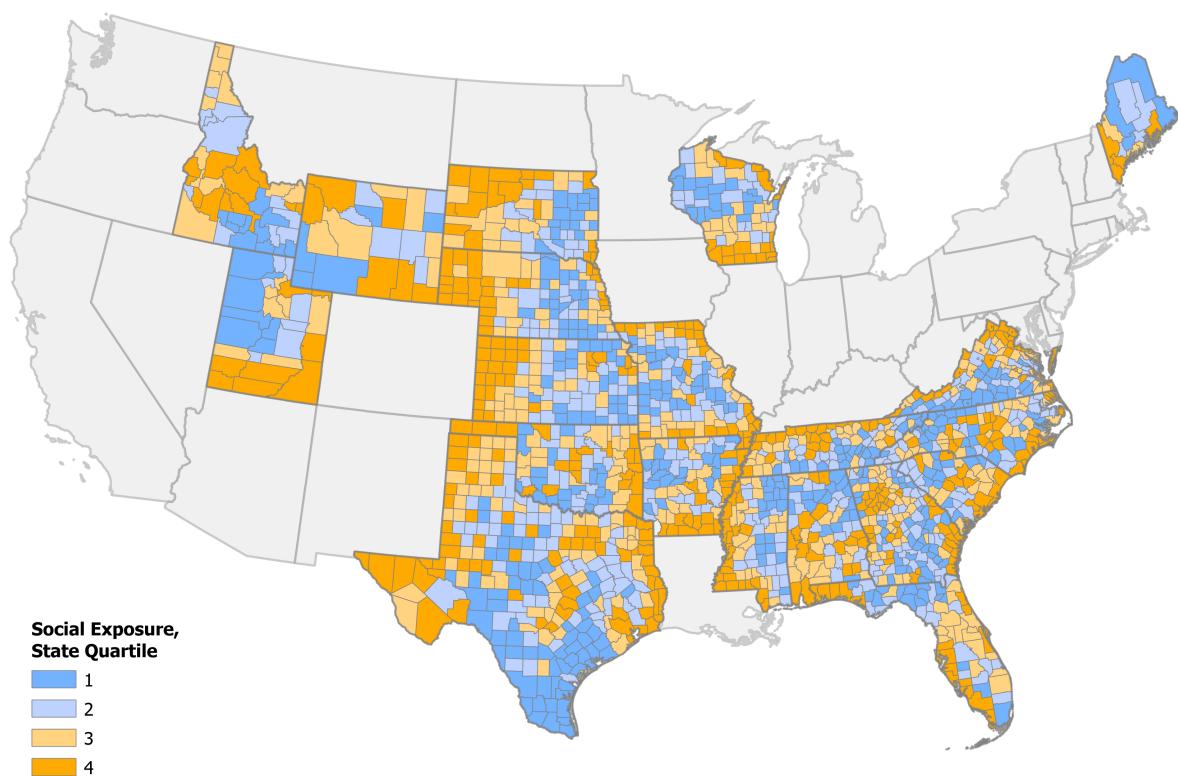
A. Enrollment among the total non-elderly adult population



B. Take-up among eligible non-elderly adults

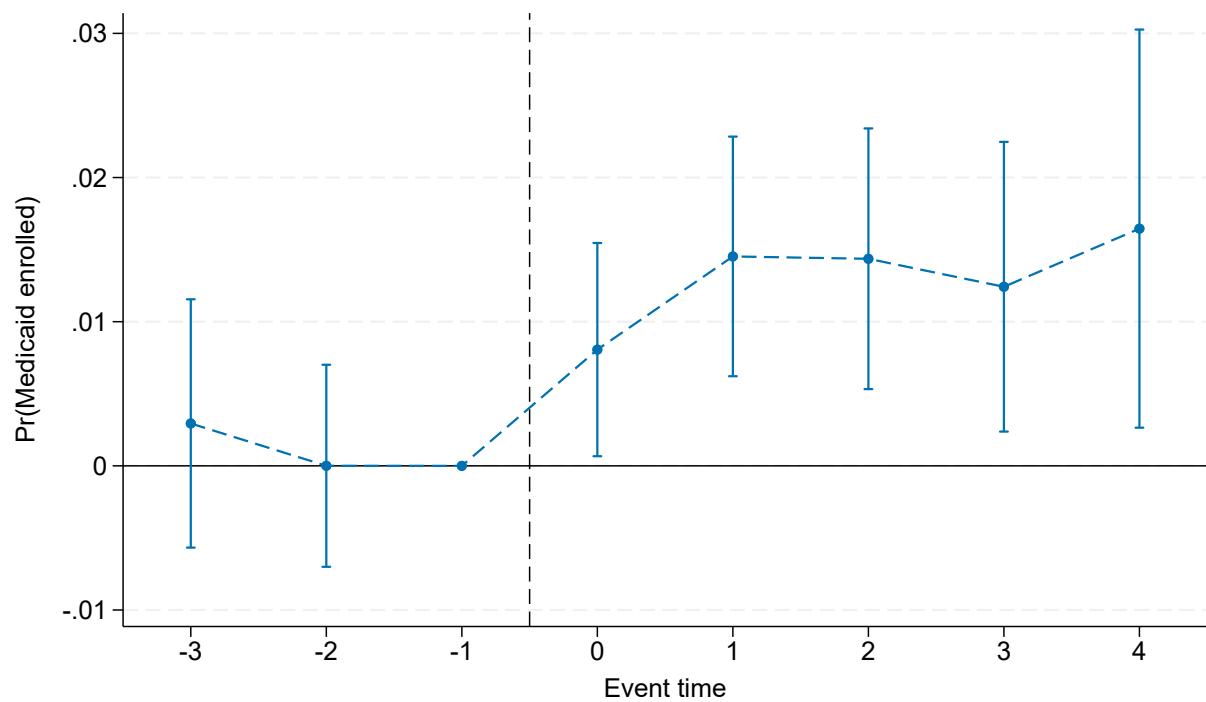
Notes: Panel A shows trends in the proportion of the overall non-elderly adult (18–64) population enrolled in Medicaid in expansion and non-expansion states. Dashed lines show the proportion enrolled in 2013 for reference. Panel B shows trends in the proportion of the eligible non-elderly adult population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

Figure 4: County-level social exposure to Medicaid expansions



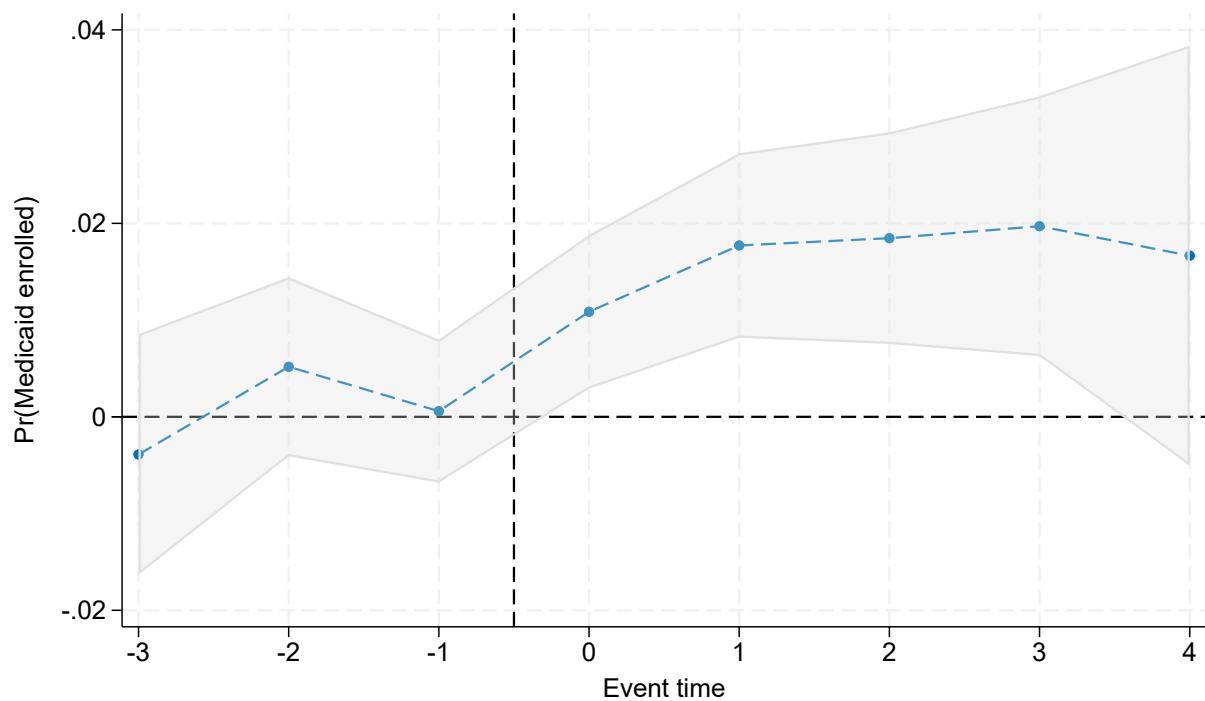
Notes: This map shows county-level social exposure to 2014–2016 Medicaid expansions in non-expansion states. Quartiles of social exposure calculated within state, with the fourth quartile representing the highest exposure.

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



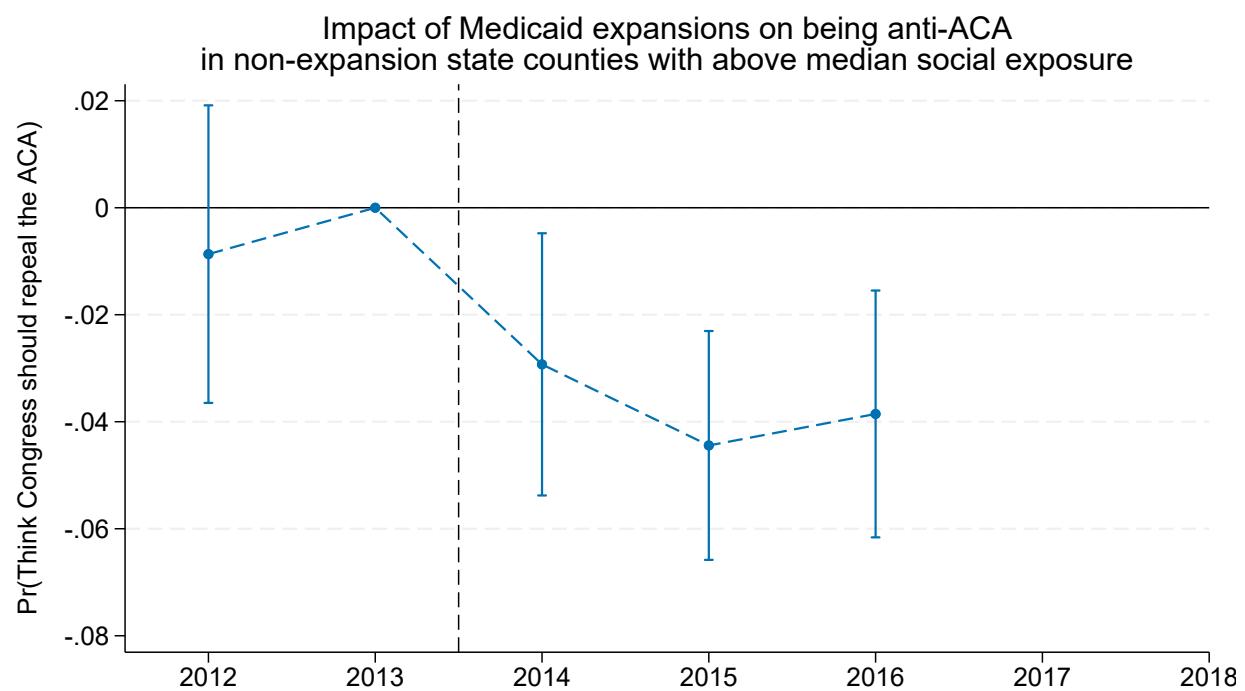
Notes:

Figure 6: Event study for impact of above-median social exposure to Medicaid expansions on insurance coverage in non-expansion states, potentially eligible adults ages 26–64 in 2012–2018



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

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



Notes:

### 3 Tables

Table 1: Effect of social network exposure on health insurance coverage by source, potentially eligible Americans ages 27-64 in non-expansion states, 2012-2018

Social Exposure	Probability of health insurance coverage from:				
	Medicaid	Medicare	Other public	Any private	Any insurance
0.013*** (0.004)	0.003 (0.003)	0.001 (0.002)	0.002 (0.005)	0.016*** (0.006)	
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	0.366	0.148	0.045	0.263	0.631
R-squared	0.094	0.145	0.081	0.126	0.121
Number of PUMAs	911	911	911	911	911
Number of observations	788,420	788,420	788,420	788,420	788,420

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

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

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

Table 3: Effect of social exposure to Medicaid expansions on preferences for state policy, American adults in non-expansion states, 2012-2018

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

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

Table 4: Effect of social exposure to Medicaid expansions on support for the Affordable Care Act, American adults in non-expansion states, 2012-2018

	Pr(Support the ACA)	
	(1)	(2)
Social Exposure (county)	-0.014 (0.011)	0.024*** (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 (0.007)	0.001 (0.010)
50k-80k	-0.009 (0.008)	-0.005 (0.011)
80k-120k	-0.015* (0.008)	-0.003 (0.011)
120k+	-0.013 (0.009)	0.006 (0.012)
Prefer not to say	-0.040*** (0.008)	-0.031*** (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