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

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Abstract

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

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1 Introduction

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

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

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

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

- Information — Social exposure to Medicaid expansions could improve ones own information about the program. As eligible people's out-of-state friends either become newly eligible and enrolled or otherwise learn more about the program, they themselves might become aware of the program or learn new information that facilitates their access.
- Stigma — Models of stigma in welfare programs typically incorporate the influence of observing others. As people see (via their online/geographically distant social networks) more people like them engaging with Medicaid, they might become more comfortable with the idea of taking the benefit themselves.
- Population support and administrative burden — In addition to influencing potentially eligible individuals' behavior directly, social network exposure could have a broader county-level impact as the general population also learns more about the program. If the general population becomes more supportive of Medicaid as a result of learning about out-of-state experiences through their social networks, then this could spur improved local administration of and advocacy for the program; on the other hand, if the general population becomes less supportive and lead to worse administrative barriers. Medicaid is a Federal-State-Local partnership, and local (e.g., county) governments often play important roles in administration (National Association of Counties, 2023).

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

Although there was no direct eligibility change in the states that didn't expand, this policy change could have had unanticipated spillovers propagated through geographically dispersed social networks. Among those in non-expansion states, already eligible individuals had different degrees of social connection to the expansion states. Given the differential pre-existing social connectedness to expansion states, the ACA policy change created a large shock to individuals' exposure to Medicaid through the experiences of their distant social networks even though there were no changes to Medicaid in their own state.

I exploit the within-state variation in pre-existing social network exposure to expansion states combined with the arguably exogenous out-of-state policy changes

I use the Facebook county-to-county Social Connectedness Index (SCI) to proxy for social connections to Medicaid expansion states among counties in non-expansion states.

I find that potentially eligible non-elderly adults in areas with stronger social connections to Medicaid expansion states were 1-2 percentage points more likely to be enrolled in Medicaid after the 2014 ACA expansions—even though eligibility did not change for these individuals—compared to other residents of the same state but living in areas with less connections to expansion states. The effect on Medicaid enrollment is reflected in the total insured rate while the probability of being covered by private insurance does not change, suggesting the results are driven by otherwise uninsured individuals becoming newly insured.

In a second strategy, I use the birthplace of individuals and their fellow household members to proxy for social connections to Medicaid expansion states. In the most stringent specification I include PUMA-year fixed effects to compare individuals within the same PUMA and with the same eligibility but different degrees of connection via birthstate to Medicaid expansions. I similarly find individuals with stronger social connections to expansion states increased probability of being enrolled in Medicaid by 1-2 percentage points following the 2014 Medicaid expansions.

To shed light on potential mechanisms driving the effect I turn to Cooperative Congressional Elections Study data to study the impact on policy preferences.

1.0.1 Possible directions for last parts of paper

The results suggest broader impacts on support for the program beyond those potentially eligible, which could impact enrollment through overall support for the program and improvements to it at the local level. Did this impact future expansions of Medicaid? Following the initial set of state expansions in 2014–2016 there was a lull in states expanding the program until the 2020s, when multiple states expanded via ballot initiative rather than legislation introduced by state lawmakers. I estimate the effect of social exposure to 2014–2016 expansions on precinct-level voting outcomes for the state ballot initiatives in recent years. [Have not done this yet—maybe out of scope for this paper?]

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

Past work on social networks and public benefit claiming has used geographic proximity interacted with language and ethnicity as a proxy for social networks. Theories of welfare stigma often include perceptions of others' use of welfare. In the main analyses, social exposure is defined with county-to-county connections in general without considering the demographic composition of the counties that are connected. While the main analyses using social connectedness index treats two individuals in the same county i as having the same probability of friendship links to county j, they could have very different personal connections. For example, if the first individual is Black and the second is white, and county j is majority white, the county level measure might not represent each individual equally. To explore this potential heterogeneity in the effect of the treatment variable I construct race/ethnicity specific social exposure variables. That is, rather than aggregating up the county-level social connectedness index by weighting by total population, as a proxy for any friend in the county, I create indexes aggregated by total race/ethnic sub-group populations.

The results highlight the importance of

1.1 Related Literature

I contribute to a few strands of literature. The issue of incomplete participation in public benefits programs among the eligible has long been of interest to economists.

- Public program take-up (Ko and Moffitt, 2022) and barriers to take-up

- Information: Wright et al. (2017) behavioral/informational nudge increased Medicaid take-up. Kenney et al. (2015) awareness of Medicaid/CHIP for children is very high among low-income uninsured parents, but only half were aware they were eligible. Wilson (2022) people with Facebook friend networks exposed to new EITC improved claiming behavior to be more optimal.
- Stigma: Stuber and Schlesinger (2006) decreases welfare and Medicaid participation through self-identity and anticipation of negative treatment. Celhay et al. (2022) use administrative links to study stigma through under-reporting, find stigma (misreporting) decreases when more local peers engaged with program. Moffitt (1983) economic model of welfare stigma.
- Administrative burden (Herd and Moynihan, 2019): Ericson et al. (2023) find streamlined enrollment reducing administrative barriers in a field experiment increased take-up of subsidized insurance. Bansak and Raphael (2007) state policy design influences take-up and crowd-out for CHIP. Fox et al. (2020) administrative rules reduction might have increased Medicaid enrollment. Wu and Meyer (2023) increased burden from poor automation of caseworker assistance decreased enrollment for SNAP, TANF, Medicaid.

- Enrollment in Medicaid
  - Woodwork effect: (Sacarny et al., 2022; Frean et al., 2017)
  - Spillovers: spillover from expanding Medicaid to increased SSI (Burns and Dague, 2017).

- Social networks and interactions with public programs Local networks (family, geographically proximate)
  - EITC: role of neighbors on (Chetty et al., 2013).
  - Welfare: effect of living with more concentrated (higher contact availability) same-language population (Bertrand et al., 2000).
  - Public prenatal care: effects with higher contact availability (by zip code) of same race/ethnic group (Aizer and Currie, 2004), results suggest not driven by information sharing.
  - Disability insurance: parent receipt in Norway increases child's future receipt (Dahl et al., 2014a).

  Broader networks (schoolmates, coworkers, geographically distant)

- EITC: impact of out-of-state Facebook friends exposed to new state EITC (Wilson, 2022), finds impact on how people claim but not whether they claim.
- Parental leave: coworkers (also brothers) in Norway more likely to take paternity leave after peer has (Dahl et al., 2014b).
- Social insurance in Norway: effects of former schoolmates (also neighbors) (Markussen and Røed, 2015).

- Geographically distant networks and local economic behavior more generally Kuchler and Stroebel (2021). Other studies using the Facebook Social Connectedness Index:
  - Hu (2022) finds distant floods impact individuals' flood insurance purchases.
  - Bailey et al. (2018b) find distant friends experiencing house price increases more likely to choose to buy homes themselves.
  - Wilson (2022) mentioned above.

- Policy diffusion and the importance of geographic networks (Linos, 2013)
  - DellaVigna and Kim (2022) polarization and policy diffusion—diffusion of policies across states was best predicted by geographic proximity in 1950–2000 but now political alignment stronger
  - Shigeoka and Watanabe (2023) policy adoption following neighbors election.
  - Shipan and Volden (2008) study mechanisms of policy diffusion for anti-smoking policy

2 Institutional Background: Medicaid and the Affordable Care Act

2.1 Medicaid: A Brief History

2.2 The ACA Medicaid Expansions

Figure 1 shows states' Medicaid expansion status as of 2018.

Figure 2 shows the growth in the number of states expanding Medicaid coverage to all low-income adults.

Figure 3 shows the trends in Medicaid enrollment in expansion states versus non-expansion states. There was a marked, approximately 20 percentage point increase in the proportion of low-income adults enrolled in Medicaid after 2014, which is not surprising given the large increase in the eligible population. However, there was also a smaller but meaningful increase of nearly five percentage points in the non-expansion states.

3 Theoretical Motivation: Public Benefits Take-Up

4 Data

4.1 Facebook Social Connectedness Index

Bailey et al. (2018a)

4.2 American Community Survey

The main data source for analysis is the Census Bureau's American Community Survey (ACS). I use ACS microdata for 2012–2018 from IPUMS (?).

The main geographic unit for all analyses using the ACS is the Public Use Microdata Area (PUMA). PUMAs are defined

4.3 Cooperative Congressional Elections Study

5 Empirical Strategies

5.1 Estimating Direct Effects of Medicaid Expansions

5.2 Estimating Indirect Social Exposure Effects

5.2.1 Alternative Social Connectedness Proxy: Birth state

6 Direct Effects of Medicaid Expansions on Enrollment

7 Social Network Exposure Effects on Medicaid Enrollment

8 Impacts on Policy Preferences and Other Mechanisms

9 Conclusion

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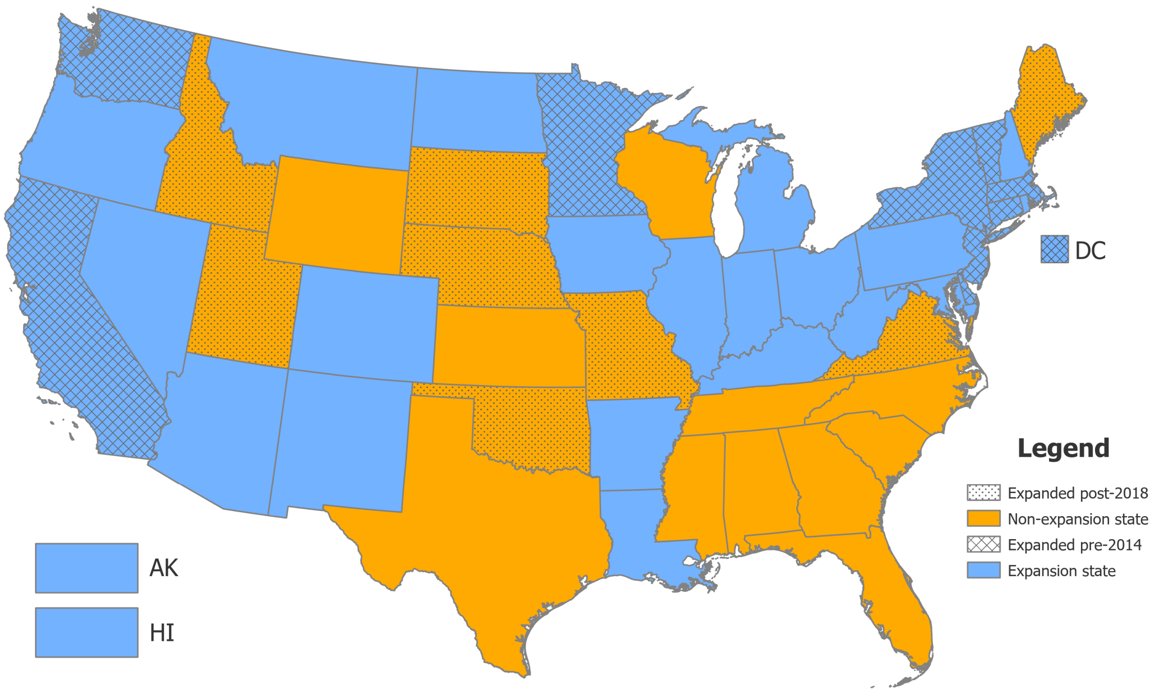
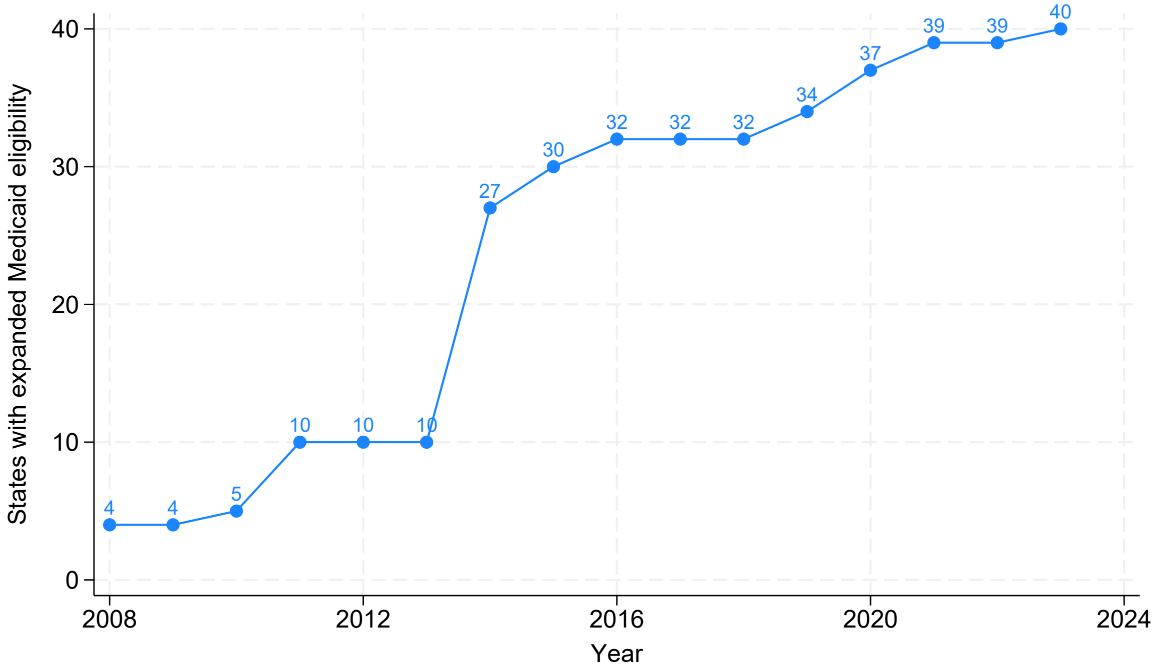
10 Figures

Figure 1: States' ACA Medicaid expansion status in 2018



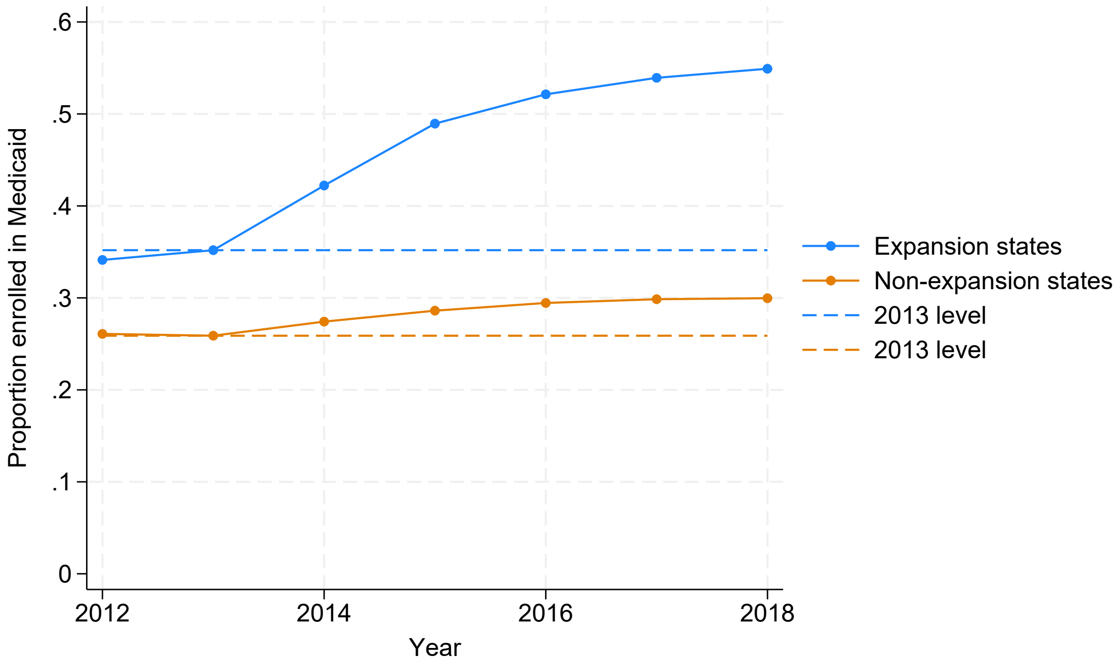
Notes: This map shows states' Medicaid expansion status—extending eligibility to all low-income (<138% poverty) adults—as of 2018. States with Medicaid programs that covered all low-income adults before the 2014 ACA expansions are defined as already expanded. Four states already had Medicaid programs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

Figure 3: Trends in low-income adults' Medicaid enrollment in expansion vs non-expansion states, 2012–2018

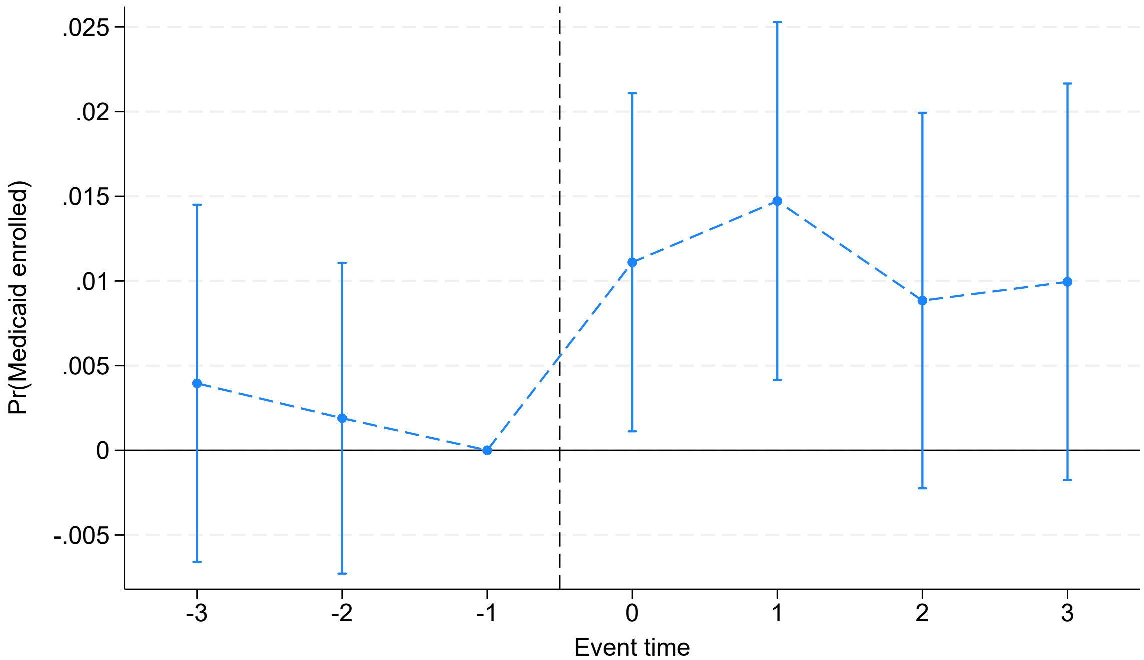


Notes: This figure shows trends in the proportion of low-income (<138% poverty) adults enrolled in Medicaid in expansion and non-expansion states. Dashed lines show the proportion enrolled in 2013 for reference.

Figure 4: Social network exposure to Medicaid expansion states among counties in non-expansion states

Notes:

Figure 5: Event study for effect of being in a high social exposure PUMA on Medicaid enrollment after Medicaid expansions



Notes:

11 Tables

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

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

Notes: *** $p < .01$, ** $p < .05$, * $p < .10$. Standard errors (in parentheses) clustered at the PUMA level. Low-income defined as below 138% of the federal poverty level. Excludes states that expanded Medicaid eligibility to all low-income adults before 2014. Individual controls include age, sex, race and ethnicity, education, and whether the respondent is a parent, married, citizen, or migrated into the state in the past year.

Table 2: Summary statistics for main analysis sample, potentially eligible adults ages 27-64 in non-expansion states

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

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

Table 3: Effect of social exposure to Medicaid expansions on insurance coverage, potentially eligible Americans ages 27-64 in non-expansion states, 2012-2018

	Health insurance coverage		
	Pr(Medicaid)	Pr(Any insurance)	Pr(Private insurance)
Social exposure (z-score)	0.011**	0.015**	0.003
	(0.005)	(0.006)	(0.005)
Individual controls	Y	Y	Y
PUMA fixed effects	Y	Y	Y
State-year fixed effects	Y	Y	Y
Outcome mean	0.398	0.627	0.217
R-squared	0.145	0.126	0.109
Number of PUMAs	911	911	911
Number of observations	428,591	428,591	428,591

Notes: *** $p < .01$, ** $p < .05$, * $p < .10$. Standard errors (in parentheses) clustered at the PUMA level. Potentially eligible defined as below the poverty line and a parent or disabled. Individual controls include age, sex, race and ethnicity, education, and whether the respondent is a parent, married, citizen, or migrated into the state in the past year.

Table 4: Effect of exposure to Medicaid expansions using birthplace as proxies for social connection, potentially eligible Americans ages 27-64 in non-expansion states, 2012-2018

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

Notes: *** $p < .01$, ** $p < .05$, * $p < .10$. Standard errors (in parentheses) clustered at the PUMA level. Potentially eligible defined as below the poverty line and a parent or disabled. Individual controls include age, sex, race and ethnicity, education, and whether the respondent is a parent, married, citizen, or migrated into the state in the past year. The five treatment groups are: born in state, born out of state in a non-expansion state, born out of state in an expansion state that expanded in 2014, 2015, and 2016.

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

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

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

12 Supplemental Exhibits

Table S1: Summary statistics for general population in non-expansion and expansion states

	Non-expansion states, PUMA social exposure				Expansion states	
	Below state median		Above state median		All	
	2012-13	2017-18	2012-13	2017-18	2012-13	2017-18
Age<18	0.24	0.23	0.24	0.23	0.23	0.22
Age 18-64	0.61	0.61	0.63	0.62	0.63	0.62
Age 65+	0.14	0.16	0.13	0.15	0.14	0.16
Male	0.49	0.49	0.49	0.49	0.49	0.49
Race/ethnicity						
NH-white	0.62	0.60	0.62	0.59	0.63	0.61
NH-Black	0.13	0.13	0.18	0.18	0.10	0.10
Hispanic	0.20	0.22	0.13	0.14	0.17	0.18
NH-other	0.05	0.05	0.07	0.08	0.10	0.11
Parental status						
Non parent	0.72	0.72	0.72	0.73	0.71	0.72
Single parent	0.09	0.09	0.08	0.08	0.08	0.08
Married parent	0.20	0.19	0.20	0.19	0.20	0.20
Disabled	0.15	0.15	0.12	0.12	0.13	0.13
Metropolitan status						
Metro, central	0.04	0.04	0.12	0.11	0.17	0.17
Metro, non-central	0.56	0.58	0.74	0.76	0.67	0.67
Non-metro	0.39	0.38	0.14	0.13	0.17	0.16
Employment status						
employed	0.44	0.46	0.47	0.49	0.46	0.49
unemployed	0.04	0.02	0.04	0.02	0.05	0.03
not in labor force	0.52	0.52	0.49	0.49	0.49	0.49
Income as % of poverty line	287.11	315.17	367.74	407.58	368.85	412.43
Any health insurance	0.81	0.86	0.84	0.89	0.87	0.93
Medicaid	0.19	0.19	0.15	0.15	0.19	0.23
Any private insurance	0.59	0.62	0.66	0.69	0.66	0.68
Observations	1225068	1252929	1144943	1211029	3875814	3940621

Notes:

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

Notes: *** $p < .01$, ** $p < .05$, * $p < .10$. Standard errors (in parentheses) clustered at the PUMA level. Potentially eligible defined as below the poverty line and a parent or disabled. Individual controls include age, sex, race and ethnicity, education, and whether the respondent is a parent, married, disabled, or migrated into the state in the past year. Continuous social exposure is the z-score of social exposure to Medicaid expansion states, which can vary over time. Binary exposure is defined as being above the state median in the 2013–2016 change in social exposure, with treatment occurring in 2014 only. Excluding friends <50mi and <200mi is the continuous measure where social exposure is constructed excluding friends that live within 50 and 200 miles, respectively.

Appendix

A Data Sources

A.1 Cooperative Congressional Elections Study

The variable "healthcare_aca" in the Cumulative CES Policy Preferences file (V3) appeared to be miss-coded for 2014–it matched the variable CC14_324_1, "vote for ACA if in congress in 2010," in the 2014 file instead of variable CC14_324_2, "vote for ACA if in congress today." In the 2014 file, the variable CC14_324_2 also appeared to be reverse coded relative to it's variable description in the data, which I confirm by comparing the cross-tabulations of the vote today and vote in 2010 variables in 2014 vs other years. I correct these miss-coded variables in the data used for my analyses.

B Social Exposure Measures

I use two versions of the SCI: county-to-county connectedness and ZIP-to-ZIP connectedness. From these I also create a few additional geography-to-geography connectedness measures at different aggregation levels. In total I use the following versions of SCI depending on the context of the analysis (referred to as Geo1-Geo2 SCI):

- **County-County:** I use the SCI measure from Facebook without any changes.
- **County-Commuting Zone:** I use the County-County SCI and aggregate County2 to the Commuting Zone level using the 2020 County2 population as the weight. To aggregate County2 to Commuting Zones I use crosswalks from Eckert et al. (2020).
- **ZIP-ZIP:** I use the SCI measure from Facebook without any changes.
- **ZIP-PUMA:** I use the ZIP-ZIP SCI and aggregate ZIP2 to the PUMA (2012 boundaries). To aggregate to the PUMA level, I use a ZIP-to-PUMA crosswalk produced by the Missouri Census Geocorr program.[1] Since ZIP and PUMA boundaries are not designed to be correspondent and often overlap, the crosswalk includes the 2020 population within each ZIP-PUMA intersection. I aggregate ZIP2 to the PUMA level using the ZIP-PUMA intersection population as the weight.
- **ZIP-State:** I use the ZIP-PUMA SCI and aggregate PUMA2 to the state level using 2020 PUMA population as the weight.
- **PUMA-PUMA:** I use the ZIP-PUMA SCI and aggregate ZIP1 to the PUMA level following the same steps as in ZIP-PUMA above.

These Geo1-Geo2 SCI measures form the base for the creation of the Social Exposure variables, which I describe below. To create the Social Exposure I aggregate each Geo2 to the total Medicaid Expansion states population as the weighted mean of the social connectedness to all Geo2 in the Expansion states. I create different variations of the Social Exposure measure using different weights for the aggregation, including total Geo2 population, Geo2 Medicaid enrolled population, and predicted change in Geo2 Medicaid enrolled population caused by ACA expansions. I also create different versions that add additional restrictions on the connected population, such as restricting to connections a certain distance away rather than just out-of-state.

B.1 Social Exposure Measure Definition and Variations

Formally, the Social Exposure measure based on Geo1-Geo2 SCI (e.g., Geo1=County and Geo2=CZ) is calculated by aggregating for each Geo1, i, the weighted sum of SCI to all Geo2, j,

$$SocExp_{it} = \sum_j \frac{w_{jt}}{w_t} SCI_{ij} \ ,$$

where $w_t = \sum_j w_{jt}$ and $w_{it} = 0$ if j is in the same state as i. I create different variations of $SocExp$ by using different weights, w_{it}.

Baseline measure: In the baseline specification,

$$w_{jt} = MedicaidExpanded_{s(j)t} Population_{j,2020} \ ,$$

[1] I use Geocorr 2022 https://mcdc.missouri.edu/applications/geocorr2022.html.

where $MedicaidExpanded$ is an indicator equal to 1 if j's state had expanded Medicaid by year t and 0 otherwise. This measure can be viewed as a proxy for the (relative) number of friends someone in i has in states that had expanded Medicaid as of year t.

Distance restricted: In a slight variation of the baseline specification, I create a version that measures the connectedness to Geo2s out-of-state and 100+ miles away, to examine the impact of removing the influence of bordering expansion counties. According to Bailey et al. (2018a), 63% of friends live within 100 miles on average, with a 10-90 percentile range of 50-75%. The mean percent of friends within 50 and 200 miles is 55% and 70%, respectively.

Medicaid enrollment weighting: The baseline measure is a proxy for connection to friends that experience the state policy overall. To create a measure that proxies for connection to individuals more directly impacted by the policy, I create a variation of the baseline measure that instead uses the weight

$$w_{jt} = MedicaidExpander_{s(j)} MedicaidCovered_{jt} \ ,$$

where $MedicaidExpander_s$ is an indicator that j is in a Medicaid expansion state (whether or not it had expanded by year t) and $MedicaidEnrolled$ is the total population covered by Medicaid in j in year t.

Predicted Medicaid enrollment weighting: The Medicaid enrolled population could change in j for many reasons. To create a measure that isolates connectedness to areas experiencing changes in Medicaid enrollment due to exogenous policy change, I use a third variation of the weight

$$w_{jt} = MedicaidExpander_{s(j)} \widehat{MedicaidCovered}_{jt} \ ,$$

where $\widehat{MedicaidCovered}_{jt}$ is the predicted number of Medicaid enrollees.

Cross-sectional measures: The above Social Exposure measures are time varying, which I use in the longitudinal analyses. However, for some analyses I do not have time variation in the outcome measure and therefor need a measure for cross-sectional analyses. In the baseline version, I use changes in Medicaid enrollment as the weights

$$w_{jt} = \delta MedicaidEnrolled_{j,t-ExpansionYear} \ ,$$

where $\delta MedicaidEnrolled$