Received: 20 October 2020 | Accepted: 19 October 2021

DOI: 10.1111/ecin.13052

ORIGINAL ARTICLE

Economic Inquiry

The effect of the Affordable Care Act Medicaid expansion on marriage

Matt Hampton[1] | **Otto Lenhart**[2]

[1]Department of Accounting, Economics, and Finance, Austin Peay State University, Clarksville, Tennessee, USA

[2]Department of Economics, University of Strathclyde, Glasgow, UK

Correspondence
Otto Lenhart, Department of Economics, University of Strathclyde, Duncan Wing, 199 Cathedral St, Glasgow, UK.
Email: ottolenhart@gmail.com

Abstract

This paper investigates the impact of the Affordable Care Act Medicaid expansions on marital behavior. We use data from the American Community Survey from 2008 to 2019 and estimate difference-in-differences models to test for effects on marriage and divorce outcomes. We find that expansions led to a 0.95% reduction in marriage stock and a 2.22% increase in divorce stock, with effects being larger among low educated individuals. We believe that two factors play a role as underlying mechanisms: (1) reduced reliance on spousal insurance coverage and (2) deciding to forego marriage or get divorced to meet eligibility restrictions.

KEYWORDS
Affordable Care Act, health insurance, marriage, Medicaid expansion

JEL CLASSIFICATION
J12, I13, D1

1 | INTRODUCTION

Sixty percentage of the nonelderly adult population in the United States receives health insurance through either employer-provided or spousal plans (Kaiser Family Foundation, 2019). Access to health insurance is thus an added benefit of being married. For those without employer-provided health insurance, however, being married can mean that family income is too high to qualify for Medicaid. In such cases, marriage could be an obstacle to getting health insurance and individuals may respond by either choosing to postpone marriage or to get divorced in order to meet Medicaid eligibility restrictions.

Medicaid expansion was one of the pillars of the Patient Protection and Affordable Care Act (ACA), a policy with the overarching goal of reducing the number of uninsured individuals in the United States. The 2014 expansions, which took place in 26 states and D.C., extended Medicaid coverage for most adults to 138% of the federal poverty level. The expansions also extended coverage to low-income, childless adults, a group historically not eligible for the program. Early work has found that ACA Medicaid expansion led to significant insurance coverage gains among those living in newly expanding states (Buchmueller et al., 2019; Courtemanche et al., 2017; Cowan & Hao, 2021). If marriage leads to Medicaid ineligibility for an individual living in a newly expanding state, it is plausible that Medicaid expansion leads to a greater share of individuals avoiding marriage or getting divorced after 2014.

Abbreviations: ACA, Affordable Care Act; CPS, Current Population Survey; DD, difference-in-differences; DDD, difference-in-differences-in-differences; PSID, Panel Study of Income Dynamics.

Managing Editor: D. Mark Anderson

In this paper, we test whether the 2014 Medicaid expansions influenced the probability of marriage and divorce. Using data from the American Community Survey (ACS) over the years 2008–2019, we examine whether the Medicaid expansions decreased the incentive to be married among people living in newly expanding states. To test this hypothesis, we follow an identification strategy recently used by Courtemanche et al. (2019) that exploits state-level variation in the decision of whether to expand Medicaid for the first time following the ACA. Using difference-in-differences (DD) models, we compare outcomes in nine "new expander" states to those in 12 "never-expander" states, that is, states that have never expanded their Medicaid programs. As a first-stage effect, we show that the 2014 expansions increased Medicaid coverage by 28.06% in new expansion states. Then, we evaluate effects of the policy on four different marital status outcomes: measures of the stock of currently married and divorced individuals as well as the flow of newly married and newly divorced. We estimate that Medicaid expansion is associated with a 0.95% reduction in the stock of currently married people, and a 2.22% increase in divorce stock. We find particularly large effects among individuals with a high school degree or less, a population subgroup likely to be impacted by Medicaid policy. For the low education subgroup, we find that Medicaid expansion is associated with a 1.54% decrease in marriage stock, and a 3.25% increase in divorce stock. While our marriage and divorce flow estimates are less consistent than findings for stock outcomes, under some specifications, namely a generalized DD model, we find significant decreases/increases in the flow of newly married/divorced following the change in policy. We believe our findings to be an indication that individuals living in states that newly expanded Medicaid as part of the ACA were less reliant on marriage to have health insurance and therefore either avoided or postponed marriage, and in some cases got divorced.

We conduct several additional analyses to show robustness of the main results, including estimating both triple differences (including a low education interaction term) and instrumental variables (treating Medicaid expansion status as an instrument for insurance coverage) models. We additionally conduct an event study approach allowing policy effects to vary across time, and a generalized DD model capturing effects of Medicaid expansion in the year that a state elects to expand their program. Finally, we test robustness of stock effects using two alternative datasets (Current Population Survey [CPS] and Panel Study of Income Dynamics [PSID]). Overall, our findings contribute to the small number of existing studies showing that certain provisions of the ACA influenced marriage decisions. In line with recent evidence on the dependent coverage mandate (Abramowitz, 2016) and the preexisting conditions provision (Hampton & Lenhart, 2019), we find that the expansions in Medicaid reduced the likelihood with which individuals are married, while increasing the likelihood of being divorced. Our findings are in contrast to the only other study evaluating effects of Medicaid expansion on marriage behavior (Slusky & Ginther, 2021), which focuses on medical divorce among a different population group, namely highly educated individuals between the ages 50 and 64.

2 | BACKGROUND

2.1 | Marriage and health insurance

Previous work provides evidence that marriage choices are influenced by policies that alter the costs and benefits of marriage. Yelowitz (1998) shows that the expansion of Medicaid eligibility beyond single-parent families significantly increased the likelihood of being married, which is an indication that individuals may have initially foregone marriage to remain eligible for public insurance. Similarly, Chen (2019) shows that becoming eligible for Medicare at age 65 is associated with a 7% increase in the likelihood of getting divorced, which suggests that the near-elderly may be particularly reliant on marriage to obtain health insurance. Other studies show that marriage decisions are influenced by changes to the Aid to Families with Dependent Children program (Moffitt, 1990) and to income taxes for married couples (Alm & Whittington, 1997, 1999).

Spousal coverage has played an important role in the US health insurance industry for decades. Berchick et al. (2018) provide an overview of the relationship between marital status and insurance. They document that many adults obtain health insurance through their spouse. In 2017, over 90% of married individuals between the ages 19 and 64 had health insurance coverage, which is substantially higher than corresponding rates among separated people (79.7%) and those who have never been married (84.0%). While spousal health insurance through an employer is very common, Fronstin and Roebuck (2014) discuss anticipated changes to the US landscape in the post-ACA period. They document that, as of 2012, 7% of employers did not cover spouses when other coverage was available to them, and that after the ACA, employers are more frequently imposing spousal surcharges when other coverage options are available. The authors contend that the recent decision by the United Parcel Service (UPS) to eliminate health benefits for spouses may be a tipping point in employment-based health benefits. UPS said that, "since the ACA requires employers to provide affordable coverage, we believe your spouse should be covered by their own employer (Fronstin & Roebuck, 2014; Hancock, 2013)." It seems likely that a potential move away from spousal coverage after passage of the ACA would reduce insurance-related marriage incentives and increase reliance on other sources of insurance, such as Medicaid.

2.2 | Impact of the ACA

Early research has examined Medicaid expansion and the ACA more generally from a variety of angles. Several studies have tested the impact of ACA Medicaid expansion on labor supply outcomes. While first finding that Medicaid expansion is associated with coverage gains, Leung and Mas (2016) and Kaestner et al. (2017) each find little to no effects on labor supply. In contrast to these studies, Peng et al. (2020) use a contiguous counties approach and find a short-run disemployment effect associated with Medicaid expansion. Other studies have examined the impact of ACA Medicaid expansion on mortality. Miller et al. (2019) and Borgschulte and Vogler (2020) each find evidence that ACA Medicaid expansion led to reductions in mortality. Other recent work has found evidence that the ACA eased financial strain related to health insurance. As a result of this, Bullinger (2021) finds that ACA Medicaid expansion led to an increase in ability of noncustodial parents to make child support payments. Similarly, in part due to eased financial strain related to health care, Hampton and Lenhart (2021) find that the ACA led to improvements in mental health among those with preexisting health conditions.

A small number of recent studies provide suggestive evidence that the ACA influenced outcomes related to marital status. Abramowitz (2016) shows that the 2010 dependent coverage provision, which allows young adults to remain on parental health insurance plans until age 26, affected marriage and divorce outcomes of young adults. Using ACS data over the period 2008–2013, the author finds that the provision led to decreases in the likelihood of marrying and decreases in spousal health insurance coverage. These findings suggest that the dependent coverage mandate reduced reliance on spousal health insurance coverage among young adults by providing an alternative source of coverage. Additionally, Abramowitz (2016) finds evidence that the probability of being divorced increased following the policy.

More recently, Hampton and Lenhart (2019) study the impact of the 2014 ACA preexisting conditions provision on marriage. Given that the provision prevents insurers from denying coverage to those with preexisting health conditions, it presumably increases health insurance options for individuals as well as decreases reliance on spousal coverage. Using longitudinal data to track individuals before and after the policy implementation, the authors find that, compared to healthy individuals, those with preexisting conditions were significantly less likely to be married and more likely to divorce following the policy. Additionally, Hampton and Lenhart (2019) find negative marriage effects among individuals with preexisting conditions covered by spousal health insurance plans prior to 2014, which furthermore indicates that these people may have been particularly reliant on their spouse to maintain health insurance coverage.

To our knowledge, the only other study that examines the effect of ACA Medicaid expansion on marital status is by Slusky and Ginther (2021). The authors find evidence that the ACA Medicaid expansions led to a decrease in medical divorce, which occurs when couples divorce so that one spouse's medical bills do not deplete the assets of the healthy spouse. They focus on a sample of college-educated individuals between the ages 50 and 64. In contrast to Slusky and Ginther (2021), we examine the effects of the expansions on marriage and divorce among all individuals aged 18–64 years, while paying particular focus on individuals with a low level of education.

Overall, previous work suggests that it is likely that the ACA expansion of Medicaid influenced marriage incentives in either of two ways: (1) individuals becoming less reliant on spousal/dependent coverage; and (2) individuals remaining unmarried or getting divorced to have family income near the new eligibility thresholds. If an individual's income is below the eligibility threshold following Medicaid expansion, it raises the value of being single. If this shift in value from being married to single is large enough, then an individual may elect to either forego marriage or seek a divorce.

3 | DATA

3.1 | American Community Survey

This study uses data from the ACS, which is a nationwide survey conducted continuously throughout each year and maintained by the US Census Bureau. The ACS is well suited to study the impact of Medicaid expansion on marriage as it contains not only information on the current marital status of individuals, but also information assessing whether individuals were newly married or divorced in the past 12 months.[1] As the study of marriage stock and flow variables may yield inconsistent results (Abramowitz & Dillender, 2017), the availability of both marriage stock and marriage flow variables is valuable for our research question. Additionally, the ACS is appealing due to its large sample size, surveying over 3 million people in any given year.

To examine the effects of the ACA Medicaid expansion on marital outcomes, we pool data from the 1-year Public Use Microdata Sample (PUMS) files between the years 2008 and 2019. We obtain these PUMS files from the Census Bureau's file transfer protocol server, which provides us with 6 years prior to and 6 years after the 2014 Medicaid expansions. To focus on a group of adults that are not yet eligible for Medicare, we restrict the sample to people aged 18–64 years. Additionally, we drop individuals that have missing information regarding marital status. Our primary sample restrictions leave us with approximately 6.5 million individuals in the full sample, and 2.5 million people with a high school degree or less.

The outcome of interest in this study is marital status. We create four indicator variables: (1) marriage stock; (2) divorce stock; (3) marriage flow; and (4) divorce flow. Marriage and divorce stock are defined as the stock of individuals currently married/divorced at any given point in time, while marriage and divorce flow capture whether individuals are newly (within the past 12 months) married/divorced. The use of both marriage/divorce stock and flow variables is in line with previous work examining effects of the ACA on marriage (Hampton & Lenhart, 2019). Studies have shown that using marriage stock as opposed to marriage flow outcomes potentially underestimates the effect of policy changes (Abramowitz & Dillender, 2017; Klerman & Haider, 2004). While it is possible that results using marriage stock yield lower bound estimates compared to a measure of flow, insight can be gained by studying stock outcomes alongside measures of flow.

3.2 | Integrated Public Use Microdata Series CPS and PSID

We complement our main analysis of marriage and divorce stock with two additional data sources: the CPS and the PSID. Integrated Public Use Microdata Series (IPUMS) March CPS Annual Social and Economic Supplement is a cross-sectional dataset maintained by the Census Bureau that harmonizes data from the CPS. The PSID is a nationally representative longitudinal survey conducted by the Survey Research Center at the University of Michigan. While IPUMS CPS and PSID do not contain survey questions capturing marriage or divorce flow, the surveys enable us to check whether our ACS estimates for marriage and divorce stock are robust to the use of alternative datasets. Both datasets contain a similar set of covariates as the ACS.[2] The CPS sample consists of annual, cross-sectional data over the years 2008–2019. The PSID is conducted biannually, and we use data over the period 2009–2019. Using the longitudinal nature of the PSID, we restrict its analysis to individuals who are present in all six survey waves. Imposing the same sample restrictions as discussed above regarding the main ACS sample leaves us with 738,240 observations for the CPS sample and 70,441 observations for the PSID sample. Finding similar marriage and divorce stock estimates using these two alternative datasets would provide further validity to our main ACS results.

4 | METHODS

4.1 | DD analysis

We employ a DD framework to estimate the average treatment effect of the ACA Medicaid expansions on marriage behavior. To provide a clear picture of state-level Medicaid expansion decisions as of 2014, Figure 1 displays a map separating states into three categories. We follow Courtemanche et al. (2019) in the definition of a treatment group of "new expander" states that did not have any previous expansion in place before 2014. These nine states are Arkansas, Kentucky, Michigan, Nevada, New Hampshire, New Mexico, North Dakota, Ohio, and West Virginia (shown in black in the figure). As shown in the figure, these nine states are geographically diverse, mitigating concerns that effects may be driven by potential regional differences in marriage and divorce. Given that we focus on evaluating effects of the 2014 expansion on marital status, we exclude states who already had Medicaid expansions in place prior to expanding their programs again as part of the ACA, or those that expanded in years later than 2014 (shown in gray in Figure 1). The main control group of our analysis consists of the 12 states that have never had any form of Medicaid expansion as of 2014. These never-expander states (shown in white in the figure) are Alabama, Florida, Georgia, Kansas, Mississippi,

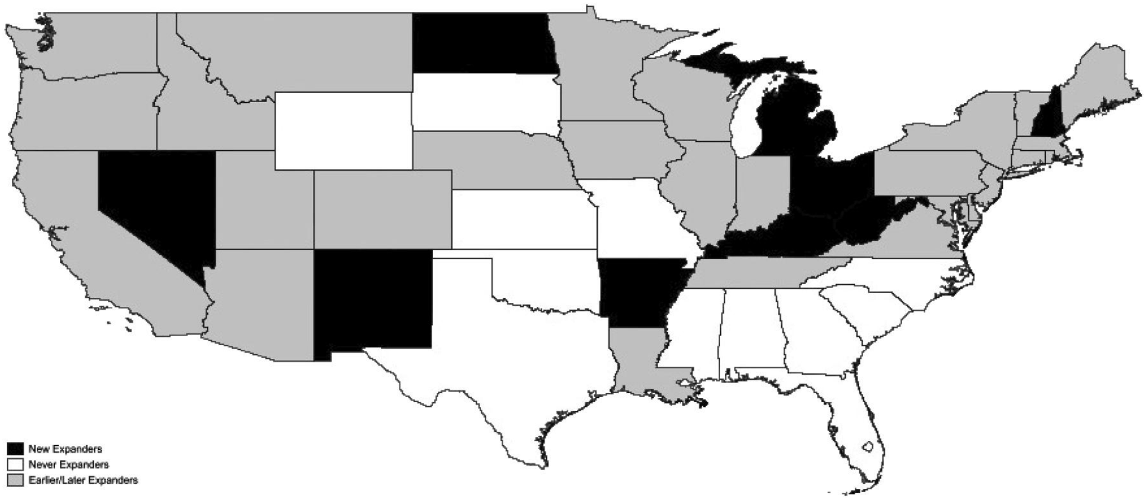

FIGURE 1 Variation in Medicaid expansion in 2014. The figure displays Medicaid expansion status as of 2014 by separating states into new expanders (black), never expanders (white), and earlier/later expanders (gray). While not shown in the figure, Alaska and Hawaii are included in the earlier/later expander group

Missouri, North Carolina, Oklahoma, South Carolina, South Dakota, Texas, and Wyoming. As a test of robustness, we additionally estimate specifications that include states with expansions of Medicaid prior to or after 2014 in the control group (these models pool white and gray states into the control group).[3]

To test for average treatment effects of the policy change on marital behavior, we estimate the model outlined by:

$$Y_{ist} = \beta_0 + \beta_1 \text{ Treat}_i + \beta_2 X_{ist} + \delta_{\text{DD}} \text{ Post}_t \times \text{Treat}_i + \beta_3 Z_{st} + \lambda_1 \text{Year}_t + \lambda_2 \text{ State}_s + \varepsilon_{ist}, \tag{1}$$

where Y_{ist} is an indicator for each of our four outcomes of interest: marriage stock, divorce stock, marriage flow, and divorce flow.[4] When examining the stock of married/divorced people, Y_{ist} equals one if individual i living in state s at time t is married/divorced, and zero otherwise. The main parameter of interest is δ_{DD}, which captures the effect of the policy change on marital status.[5] When examining whether the expansions led to changes in the flow of either marriage or divorce, Y_{ist} equals one if the respondent had a change to his or her marital status (either married or divorced in separate specifications) in the prior 12 months, and zero otherwise. As a first-stage analysis of insurance coverage gains from the 2014 expansions, we estimate specifications in which Y_{ist} equals 1 if the respondent is covered by Medicaid, and zero otherwise. Treat_i equals one if the individual lives in one of the new expander states, while Post_{ist} equals one in the post-treatment period (after 2014) and zero in the pre-treatment years (before 2014).

The vector X_{ist} contains observable characteristics at the individual level such as age, gender, race, and education. Z_{st} accounts for several time-varying state-level controls that could related to health insurance coverage. In addition to state unemployment rates and an indicator for the presence of state-level Earned Income Tax Credit laws, Z_{st} also controls for variations in the implementation of the following ACA provisions: (1) Medicaid expansions; (2) Community First Choice Medicaid options, which allow states to provide community-based support for individuals with disabilities; (3) Home and community-based services, which give states additional options for providing home and community services through Medicaid state plans, primarily for people with mental health needs; (4) an indicator for whether states allow the sale of "grandfathered" insurance plans that had been in existence prior to the ACA; and (5) state-level dependent coverage mandate laws.

Several components of Equation (1) warrant further discussion. One concern is that unobservable characteristics at the state level might cause divorce to spike in certain states if individuals making up the treatment group disproportionately live in these states. To mitigate this concern, we include state fixed effects, denoted by State_s. Additionally, to account for unobservable characteristics across time, we include year fixed effects denoted by Year_t. We estimate each of the DD specifications using linear probability models, with standard errors clustered at the state level. Due to the relatively small number of clusters, we apply a wild cluster bootstrap resampling method with 1000 replications proposed by Cameron et al. (2008). The authors show that standard asymptotic tests can over-reject the null in the presence of only a few clusters and introduce an alternative method to account for within-group dependence when estimating standard errors.[6]

To test for year-by-year effects of the Medicaid expansion on marital decisions, we augment Equation (1) and estimate the following specification:

$$Y_{ist} = \beta_0 + \beta_1 \text{ Treat}_i + \beta_2 X_{ist} + \sum_{t=2008}^{2019} \delta_t \text{Year}_t \times \text{Treat}_i + \beta_3 Z_{st} + \lambda_1 \text{Year}_t + \lambda_2 \text{ State}_s + \varepsilon_{ist}, \tag{2}$$

where the year indicators (Year_t) are interacted with the treatment indicator (Treat_i). The excluded reference category is the year prior to the change in policy (2013). Besides differentiating between contemporaneous and lagged effects of the policy, estimating the event study model allows us to test for the presence of similar trends in marital status during the pre-treatment years, which is the assumption governing any DD model. A statistically significant estimate of Year_t pertaining to the years prior to the reform provides suggestive evidence of differential trends between the treatment and control groups (conditional on covariates), and would violate the standard pre-treatment trends assumption. As well as this, the event-study style model may shed light on whether marriage effects are only temporary, or are persistent across time.

4.2 | DDD analysis

Due to the nature of the eligibility rules for Medicaid, low-income households living in expansion states are the group that is most likely to benefit from the policy change. While our main DD model evaluates the overall effects of the expansions on marriage behavior, we additionally estimate difference-in-differences-in-differences (DDD) specifications which take into account differences in exposure to the policy changes across the population. Specifically, we use an indicator for low education (having a high school degree or less) for the DDD analysis, where higher educated individuals in both treatment and control states serve as an additional comparison group. We estimate the following specification:

$$\begin{aligned} Y_{ist} = {} & \beta_0 + \beta_1 \text{ Treat}_i + \beta_2 \text{ LowEd}_{ist} + \beta_3 \text{ Post}_t \times \text{Treat}_i + \beta_4 \text{ Post}_t \times \text{LowEd}_{ist} + \beta_5 \text{ Treat}_i \times \text{LowEd}_{ist} + \delta_{\text{DDD}} \text{ Post}_t \\ & \times \text{LowEd}_{ist} \times \text{Treat}_i + \beta_6 X_{ist} + \beta_7 Z_{st} + \lambda_1 \text{Year}_t + \lambda_2 \text{State}_s + \varepsilon_{ist}, \end{aligned} \tag{3}$$

where LowEd is an indicator that equals one if an individual has completed no more than a high school degree and zero otherwise. While all other variables remain the same as in Equation (1), the main parameter of interest is δ_{DDD}. Estimates obtained in the DDD analysis can provide supportive evidence for the DD results and remove concerns that the DD effects are driven by other changes occurring at the time that affected all individuals, independent of their Medicaid eligibility status.

4.3 | Robustness checks

We also conduct several robustness checks. First, we estimate an IV model for which Medicaid expansion status serves as an instrument. The effects of expanding Medicaid in 2014 on health insurance coverage serves as the first-stage effect, while the reduced form estimates provide evidence for the effects of insurance coverage on marriage outcomes. Finding IV effects that are consistent with the DD/DDD results can provide further evidence of the robustness of our main analysis.

Second, we estimate a generalized DD model that includes all 51 states. While our main analysis focuses on examining the effects of the 2014 Medicaid expansions, this robustness check is able to incorporate staggered expansions prior to and following the ACA. In this model, the variable of interest is an indicator of Medicaid expansion status that captures the staggered rollout of Medicaid policy across states and time. In a third robustness check, we change the makeup of the control group by including earlier/later expanders. Showing that the main estimates are robust to a variety of control group selections lends suggestive evidence that results are not sensitive to only a narrow set of definitions.

Fourth, we follow Slusky (2017) in the estimation of a series of "rolling window" placebo tests. In these tests, we take four different 5-year windows (2008–2012, 2009–2013, 2010–2014, 2011–2015) and impose artificial Medicaid expansions in the years 2010, 2011, 2012, and 2013 in the states that form our treatment group. In addition to mitigating concerns that the results are driven by other factors, finding no statistically significant differences in marriage behavior between treatment and control groups also provides suggestive evidence that the DD "parallel trends" assumption is satisfied. Finally, we include a placebo test that estimates the effects of the expansion on marriage behavior among individuals aged 65 and above, a group that is eligible for Medicare and thus should not be affected by changes to Medicaid eligibility.

4.4 | Descriptive statistics

To assess the impact of Medicaid expansion on marital outcomes, it seems warranted to provide evidence of a first-stage increase in Medicaid coverage in new expander states. Figure 2 confirms that the 2014 policy substantially increased the share of individuals covered by Medicaid living in newly expanding states relative to never-expanding states. The graph suggests that the expansions immediately influenced insurance coverage among individuals in states that newly expanded Medicaid in 2014. This increase is further reflected in Table 1, which provides summary statistics for new expander states and states that have never had an expansion. While the share of respondents covered by Medicaid prior to 2014 is slightly larger in new expander states prior to 2014, a substantial gap is observable after the expansion, which confirms that the policy significantly affected insurance coverage in treated states.[7] Table 1 further shows that across new expander and never-expander states, individuals are quite comparable in terms of age and sex. From the table, individuals residing in new expansion states are more likely to be white, and slightly less likely to be employed and attend college.

To get a graphical sense for whether Medicaid expansions influence marital outcomes, Figure 3 plots the four measures of marital status across time in both new expander and never-expander states. Figure 3a shows that, while the proportion of currently married individuals was slightly higher in new expander states prior to the policy, a noticeable trend disruption exists after 2014. By 2017, the proportion of married individuals is shown to be larger in never-expander states. Additionally, Figure 3a shows that marriage stock trends were almost identical between the treatment and control groups throughout the pre-policy period (2008 to 2013). This provides suggestive evidence that the DD "parallel trends" assumption is satisfied for the marriage stock outcome.

Figure 3b shows analogous trends for the divorce stock outcome. Again, prior to 2014, trends in divorce stock are parallel between those living in new expander and never-expander states. Following 2014, there again appears to be a trend disruption, with new expander states showing an increase in divorce stock, and never-expander states showing a decrease. This additionally lends support to the idea that the 2014 ACA Medicaid expansion impacted the stock of married and divorced people.

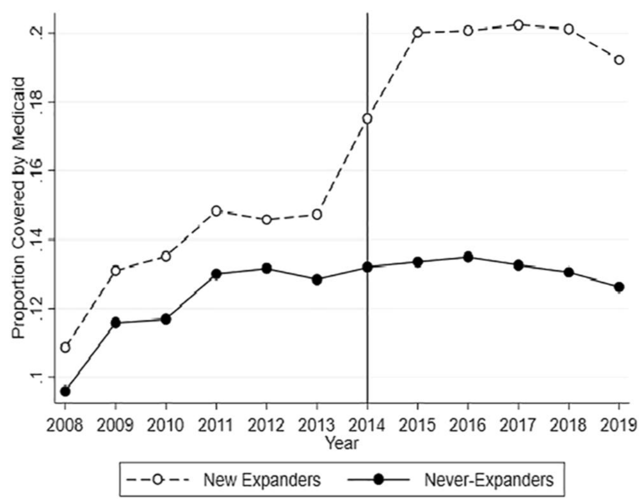

FIGURE 2 Proportion covered by Medicaid across time. Sample includes all individuals aged 18–64 years. Figure displays the proportion of individuals covered by Medicaid in new expander (dashed line) and never-expander (solid line) states across time. The vertical line at 2014 represents the initial year of Affordable Care Act Medicaid expansion. *Source*: American Community Survey 1-year Public Use Microdata Sample files, 2008–2019

TABLE 1 Descriptive statistics

Variable	New expanders	Never-expanders	*t*-stat
Medicaid coverage			
Pre	0.136	0.120	40.751
Post	0.195	0.132	145.394
Marriage stock			
Pre	0.770	0.764	12.219
Post	0.765	0.765	−1.005
Divorce stock			
Pre	0.176	0.169	14.484
Post	0.182	0.171	21.938
Marriage flow			
Pre	0.029	0.031	−12.063
Post	0.031	0.034	−12.404
Divorce flow			
Pre	0.017	0.017	−3.142
Post	0.015	0.015	−0.167
Age	47.285	46.677	62.792
Male	0.471	0.467	9.549
Employed	0.710	0.716	−13.099
White	0.879	0.793	259.804
Black	0.057	0.120	−2.400
Other race	0.064	0.087	−98.181
Low education	0.399	0.377	53.013
High education	0.601	0.623	−53.013
Unemployment rate	6.904	6.322	281.259
State EITC (% of federal)	0.044	0.014	673.263
Refundable state EITC	0.286	0.146	423.167
Community first choice Medicaid option	0.000	0.144	−5.700
Home- and community-based services	0.122	0.111	40.228
Dependent coverage mandate laws	0.279	0.566	−6.900
Grandfathered plans renewal	0.919	1.000	−6.400
Observations	1,912,053	4,611,848	-

Note: Sample means for new expander and never-expander states along with test statistics of statistical differences. Sample includes all individuals aged 18–64 years.

Abbreviation: EITC, Earned Income Tax Credit.

Source: American Community Survey 1-year Public Use Microdata Sample files, 2008–2019.

Suggestive evidence of changes in marriage and divorce flow is more nuanced. Figure 3c,d shows analogous plots for the two flow measures of marital status. From Figure 3c, pre-treatment marriage flow trends appear to be very similar for each group, with the recent entrance of new individuals into marriage being larger among those living in never-expanding states. Just as was the case with marriage stock in the previous figure, after 2014 there is a noticeable

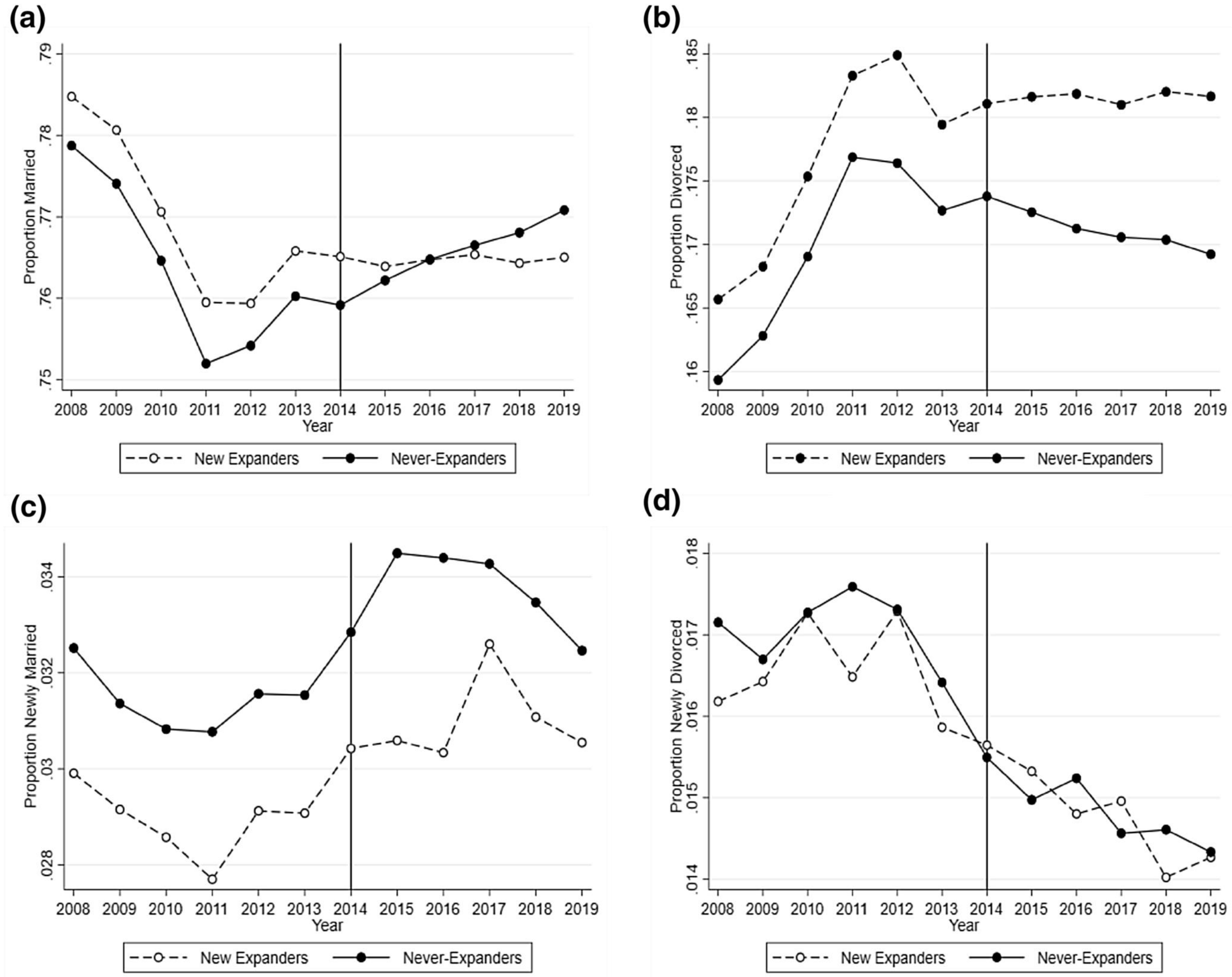

FIGURE 3 Effect of Affordable Care Act (ACA) Medicaid expansion on marital outcomes. (a) Marriage stock, (b) divorce stock, (c) marriage flow, and (d) divorce flow. Sample includes all individuals aged 18–64 years. Figures display changes in marital status outcomes in new expander (dashed lines) and never-expander (solid lines) states across time. The vertical line at 2014 represents the initial year of ACA Medicaid expansion. *Source*: American Community Survey 1-year Public Use Microdata Sample files, 2008–2019

"leveling off" of marriage flow among those living in new expander states, relative to never-expanders. From the figure, this leveling of marriage flow persists until 2017, when visually there is a sharp rebound of marriage entrance for those in new expander states. This rebound in marriage flow is only temporary, with the proportion newly married showing large decreases into the 2018 and 2019 years. The temporary rebound in marriage flow among those in new expansion states in 2017 is difficult to rationalize, however it might imply that any effects on marriage flow are only short term, or perhaps that individuals are temporarily foregoing/delaying their marriage entrances in response to the change in policy.

Finally, Figure 3d shows a plot of the flow of newly divorced individuals across time. Unlike the previous figures, for the divorce flow outcome, the pre-treatment trends appear noisy, and there is no discernable effect following 2014. Overall, divorce flow appears to be very similar in both new expander states and never-expander states over the entire period. Given that little can be taken away from the divorce flow figure, this may imply that Medicaid expansion influences the decision to get married, while having less impact on divorce decisions of those already married. As foregoing marriage may be relatively costless when compared to divorce, it is intuitive that Medicaid expansion may have a larger impact on marriage rather than divorce flow.

5 | RESULTS

5.1 | First-stage effect on Medicaid coverage

Table 2 shows estimates for the first-stage effects of the policy change on Medicaid coverage for both the full sample and those with low education. From Panel A, we find that individuals living in treated, new expander states are 3.81 percentage points ($p < .01$) more likely to be covered by Medicaid in the post-policy period compared to those in never-expander states, which corresponds to a 28.06% increase compared to before 2014. Column (2) presents estimates for the low education sample. Among those with a high school degree or less, we estimate a 5.98 percentage point (30.59%) increase in Medicaid coverage following the policy, indicating that those with low education may be more responsive to any changes in Medicaid policy.[8]

Table 2, Panel B displays the annual treatment effects from estimating Equation (2) for both the full sample and those with low education (Figure 4 shows the corresponding event study plot for the full sample). Again, each model includes state and year fixed effects as well as demographic and state-level covariates, and 2013 is omitted as the reference category. All event-study plots display estimated coefficients along with 95% confidence intervals. Additionally, the figures show a baseline of zero (the solid horizontal line) and the mean across all survey waves (the dotted horizontal line). From Figure 4, while the 2008–2012 estimated coefficients are statistically indistinguishable from zero, from 2013 to 2014 there is a noticeably sharp increase in Medicaid coverage, with the change in coverage leveling off from 2015 to 2019. Panel B of Table 2, which corresponds to Figure 4, shows the significant increases in Medicaid coverage following 2014, with particularly large coverage gains among those living in new expander states. We find little to no differential effects between the two groups in the pre-treatment years, whereas in post-expansion years, the observed effects are positive and statistically significant (all $p < .01$). Besides further confirming the first-stage effects of the policy on insurance coverage, these findings also suggest that pre-treatment trends in Medicaid coverage were similar across both groups.[9]

5.2 | Effect on marriage behavior

Table 3 presents our DD estimates for the effects of the Medicaid expansion on marital outcomes among the full sample (Panel A) and for those with low education (Panel B). Columns (1) and (2) reflect that among both the low education and full samples, Medicaid expansion is associated with significant reductions in marriage stock and significant increases in divorce stock. Among the full sample, we find that Medicaid expansion leads to a 0.73 pp (0.95%) reduction in marriage stock, and a 0.39 pp (2.22%) increase in divorce stock. Effects are larger in magnitude for the low education sample. For those with low education, we estimate that Medicaid expansion is associated with a 1.12 pp (1.54%) reduction in marriage stock, and a 0.65 pp (3.25%) increase in divorce stock. These findings are in line with the graphical images of Figure 3 and provide evidence that 2014 Medicaid expansion impacted marriage and divorce stock.[10,11]

Results for the flow of newly married and divorced people are less clear. From Table 3, Column (3), while negative in sign, there is no statistically significant effect of Medicaid expansion on marriage flow among either the full sample or those with low education. For the divorce flow outcome [presented in Column (4)], we find that Medicaid expansion is associated with a 0.05 pp increase in divorce flow among the full sample ($p < .10$), and a 0.07 pp increase among those with low education ($p < .10$). While significant at only the 10% level, these findings indicate that Medicaid expansion is associated with increases in being newly divorced for those in new expander states. Overall, the results in Table 3 suggest that individuals living in newly expanding states were less likely to be currently married and more likely to be currently divorced following 2014 when compared to individuals in never-expanding states.[12]

To assess the year-by-year effects of the policy on marriage and divorce stock, Table 4 displays event study estimates outlined by Equation (2), both among the full sample and those with low education. Comparing marriage and divorce stock outcomes in each year to that of the baseline year of 2013, the table shows that prior to the policy change, there were no statistically significant differences in outcomes between new expander and never-expanding states. This shows evidence that the standard pre-treatment trends assumption is satisfied. From Table 4, several of the post policy interactions are statistically significant, with negative effects on marriage stock and positive effects on divorce stock. Panel B displays that for the low education sample. Effect magnitudes are quite a bit larger for those with low education than among the full sample.

TABLE 2 The effects of Medicaid expansion on Medicaid coverage

	Full sample (1)	Low education (2)
Panel A: DD effect		
Wild cluster bootstrap *p*-value	.0381***	.0598***
	[.000]	[.000]
Panel B: Annual effects		
Treat × 2008	−.0061	−.0074
	[.122]	[.208]
Treat × 2009	−.0037	−.0034
	[.279]	[.579]
Treat × 2010	−.0002	−.0027
	[.936]	[.582]
Treat × 2011	.0008	−.0007
	[.731]	[.844]
Treat × 2012	−.0045**	−.0080**
	[.031]	[.016]
Treat × 2014	.0164**	.0244**
	[.017]	[.029]
Treat × 2015	.0394***	.0584***
	[.000]	[.000]
Treat × 2016	.0389***	.0594***
	[.000]	[.000]
Treat × 2017	.0416***	.0664***
	[.000]	[.000]
Treat × 2018	.0424***	.0670***
	[.000]	[.000]
Treat × 2019	.0379***	.0669***
	[.000]	[.000]
Sample mean	.1358	.1955
Observations	6,523,901	2,499,017

Note: Sample includes all individuals aged 18–64 years. Panel A shows estimated coefficients from the DD model outlined by Equation (1), while Panel B displays event study estimates from the model outlined by Equation (2). Dependent variable is a Medicaid coverage dummy. All specification use the wild cluster bootstrap procedure with 1000 replications to estimate *p*-values, as proposed by Cameron et al. (2008). Wild cluster bootstrap *p*-values are shown in brackets.

Abbreviation: DD, difference-in-differences.

$^{***}p < .01$, $^{**}p < .05$.

Source: American Community Survey 1-year Public Use Microdata Sample files, 2008–2019.

Figure 5 shows the analogous event-study estimates of Equation (2) for both stock and flow outcomes. From Figure 5a,b, there are discernable changes in both marriage and divorce stock following the change in policy. Following Medicaid expansion, there appears to be a significant reduction in the stock of married people, and a significant increase in the stock of divorced individuals among those living in new expander states. From Figure 5c,d, visual results for flow outcomes are less clear, with all estimated coefficients statistically indistinguishable from zero. Taken together,

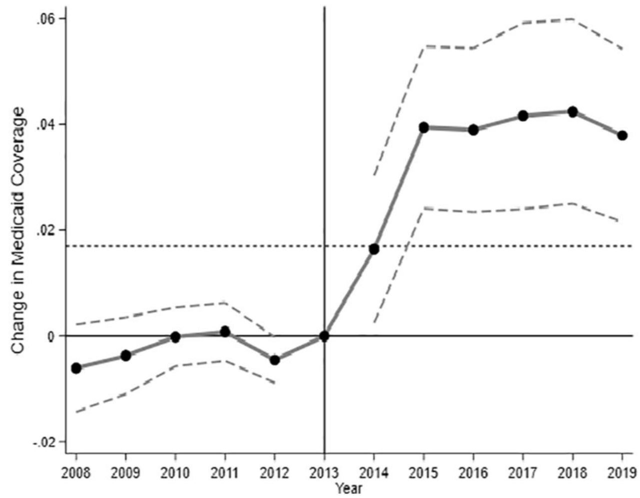

FIGURE 4 Event study effects of Affordable Care Act (ACA) Medicaid expansion on Medicaid coverage. Sample includes all individuals aged 18–64 years. Figure displays estimated coefficients (black dots) from the event study model outlined by Equation (2). Dependent variable is a Medicaid coverage dummy. The horizontal solid line represents the baseline of zero, while the horizontal dotted line represents the mean across all years. The dashed lines represent 95% confidence intervals. Coefficients are relative to 2013

TABLE 3 The effects of Medicaid expansion on marital status

	Marriage stock (1)	Divorce stock (2)	Marriage flow (3)	Divorce flow (4)
Panel A: Full sample				
DD effect	−.0073**	.0039**	−.0005	.0005*
	[.010]	[.027]	[.393]	[.089]
Sample mean	0.7703	0.1760	0.0289	0.0166
Observations	6,523,901	6,523,901	6,523,901	6,523,901
Panel B: Low education				
DD effect	−.0112***	.0065**	−.0000	.0007*
	[.002]	[.014]	[.838]	[.081]
Sample mean	0.7270	0.1999	0.0262	0.0176
Observations	2,499,017	2,499,017	2,499,017	2,499,017

Note: Sample includes all individuals aged 18–64 years (Panel A) and all individuals aged 18–64 years with a high school degree or less (Panel B). Estimated coefficients are from the DD model outlined by Equation (1). Marital status-dependent variables are denoted at the top of each column. All specification use the wild cluster bootstrap procedure with 1000 replications to estimate *p*-values, as proposed by Cameron et al. (2008). Wild cluster bootstrap *p*-values are shown in brackets.

Abbreviation: DD, difference-in-differences.

***$p < .01$, **$p < .05$, *$p < .10$.

Source: American Community Survey 1-year Public Use Microdata Sample files, 2008–2019.

the results from both Table 4 and Figure 5 show evidence of significant policy effects on both marriage and divorce stock, while less can be taken away regarding changes in marriage/divorce flow.

5.3 | DDD and IV analysis

Because individuals with low education are especially likely to be impacted by Medicaid policy, as a test of robustness we estimate the triple difference model outlined by Equation (3). Presented in Table 5 are estimated coefficients of the triple interaction between indicator variables for living in a new expander state, having a high school degree or less, and

TABLE 4 Annual treatment effects on marriage and divorce stock

	Panel A: Full sample		Panel B: Low education	
	Marriage stock (1)	Divorce stock (2)	Marriage stock (3)	Divorce stock (4)
Treat × 2008	.0020	−.0015	.0018	−.0022
	[.392]	[.568]	[.653]	[.580]
Treat × 2009	.0033	−.0028	.0026	−.0030
	[.242]	[.193]	[.657]	[.592]
Treat × 2010	.0011	−.0013	−.0008	−.0004
	[.633]	[.589]	[.729]	[.871]
Treat × 2011	−.0009	.0008	−.0043	.0030
	[.664]	[.670]	[.149]	[.181]
Treat × 2012	−.0011	.0018	−.0015	.0009
	[.627]	[.330]	[.675]	[.748]
Treat × 2014	.0001	.0002	−.0044	.0043
	[.961]	[.901]	[.264]	[.226]
Treat × 2015	−.0045*	.0019	−.0093***	.0032
	[.072]	[.397]	[.000]	[.132]
Treat × 2016	−.0068*	.0040*	−.0132***	.0087***
	[.046]	[.069]	[.001]	[.000]
Treat × 2017	−.0082**	.0043*	−.0127**	.0058
	[.019]	[.051]	[.017]	[.118]
Treat × 2018	−.0102***	.0052**	−.0122***	.0072**
	[.000]	[.011]	[.001]	[.029]
Treat × 2019	−.0109***	.0050**	−.0194***	.0089**
	[.000]	[.030]	[.000]	[.014]
	6,523,901	6,523,901	2,499,017	2,499,017

Note: Sample includes all individuals aged 18–64 years (Panel A) and all individuals aged 18–64 years with a high school degree or less (Panel B). Estimated coefficients are from the event study model outlined by Equation (2). Marital status-dependent variables are denoted at the top of each column. All specifications use the wild cluster bootstrap procedure with 1000 replications to estimate p-values, as proposed by Cameron et al. (2008). Wild cluster bootstrap p-values are shown in brackets.

***$p < .01$, **$p < .05$, *$p < .10$.

Source: American Community Survey 1-year Public Use Microdata Sample files, 2008–2019.

a post-policy dummy. Three of the four marital outcomes are significant at the highest conventional level, with coefficient signs all being in anticipated directions. While we find no significant effects on marriage flow, we estimate that following the Medicaid expansion, there were significant reductions in marriage stock, and increases in both divorce stock and divorce flow (all $p < .01$) among those with low education levels. This lends further support to the idea that Medicaid expansion impacted marriage and divorce outcomes among the low educated.

As an additional test of robustness, we test for policy effects by estimating an IV model, which treats 2014 Medicaid expansion status as an instrument for insurance coverage. The reduced form results from the IV analysis are presented in Table 6. In line with both the DD and the DDD results, we again find that the expansions significantly affected people's marriage outcomes. We show that newly gained access to insurance decreases marriage stock ($p < .01$), increases divorce stock ($p < .05$), while also leading to a reduction in divorce flow ($p < .10$). The first-stage F-statistic for the IV analysis is 527, which is consistent with the large and statistically significant first-stage effects shown in our DD analysis (Table 2).

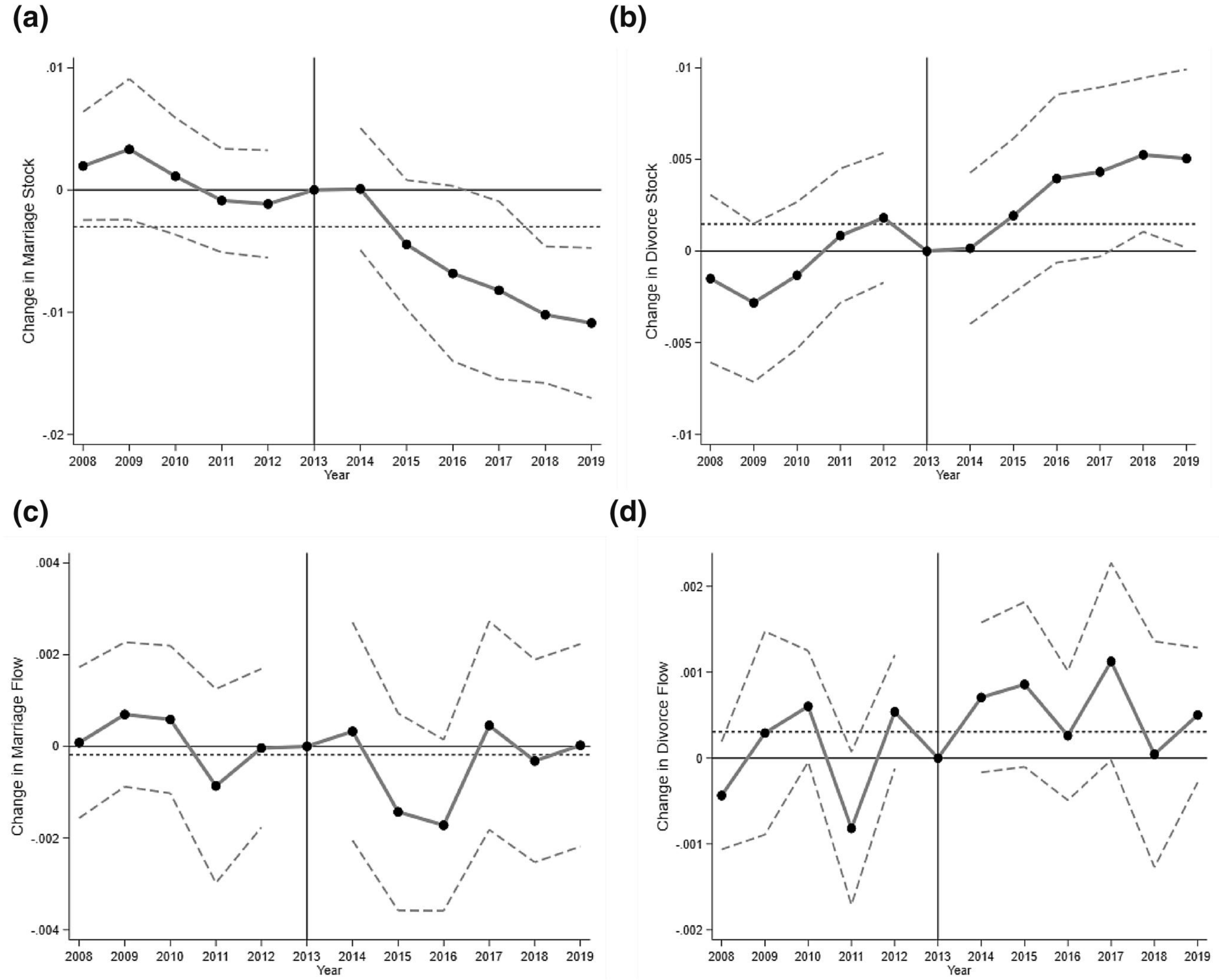

FIGURE 5 Event study effects of Medicaid expansion on marital outcomes. (a) Marriage stock, (b) divorce stock, (c) marriage flow, and (d) divorce flow. Sample includes all individuals aged 18–64 years. Figures display estimated coefficients (black dots) from the event study model outlined by Equation (2). Marital status dependent variables are indicated below each figure. The horizontal solid line represents the baseline of zero, while the horizontal dotted line represents the mean across all years. The dashed lines represent 95% confidence intervals. Coefficients are relative to 2013. *Source*: American Community Survey 1-year Public Use Microdata Sample files, 2008–2019

5.4 | Other robustness checks

5.4.1 | Alternative group definitions

Studying the effects of Medicaid expansion requires one to make sometimes difficult choices regarding the makeup of treatment and control groups. While the identification strategy of Courtemanche et al. (2019) offers perhaps the "cleanest" treatment effect by comparing individuals living in new expander states to those in states that have never expanded, it is important to estimate effects across a variety of group definitions. Table 7 displays results from estimating a generalized DD model that includes an indicator variable that captures a state's ACA Medicaid expansion status in the year of expansion. This model includes all 50 states as well as the District of Columbia, which results in a full sample containing over 15 million observations, and a low education sample of almost 6 million. From the table, marriage and divorce stock results remain robust, with effects being slightly larger in magnitude

TABLE 5 The effects of Medicaid expansion on marital status DDD model

	Marriage stock (1)	Divorce stock (2)	Marriage flow (3)	Divorce flow (4)
DDD effect	−.0223***	.0250***	.0012	.0023***
	[.000]	[.000]	[.224]	[.000]
Sample mean	0.7703	0.1760	0.0289	0.0166
Observations	6,523,901	6,523,901	6,523,901	6,523,901

Note: Sample includes all individuals aged 18–64 years. Estimated coefficients are from the DDD model outlined by Equation (3). Marital status-dependent variables are denoted at the top of each column. All specifications use the wild cluster bootstrap procedure with 1000 replications to estimate *p*-values, as proposed by Cameron et al. (2008). Wild cluster bootstrap *p*-values are shown in brackets.

Abbreviation: DDD, difference-in-differences-in-differences.

***$p < .01$.

Source: American Community Survey 1-year Public Use Microdata Sample files, 2008–2019.

TABLE 6 The effects of Medicaid expansion on marital status IV model

	Marriage stock (1)	Divorce stock (2)	Marriage flow (3)	Divorce flow (4)
Panel A: Full sample				
IV effect	−.1924***	.1015**	−.0140	.0143*
	[.000]	[.012]	[.332]	[.082]
Sample mean	0.7703	0.1760	0.0289	0.0166
Observations	6,523,901	6,523,901	6,523,901	6,523,901
Panel B: Low education				
IV effect	−.1869***	.1088**	−.0007	.0111
	[.000]	[.010]	[.980]	[.127]
Sample mean	0.7270	0.1999	0.0262	0.0176
Observations	2,499,017	2,499,017	2,499,017	2,499,017

Note: Sample includes all individuals aged 18–64 years (Panel A) and all individuals aged 18–64 years with a high school degree or less (Panel B). The first-stage *F*-statistic is 527.06. Estimated coefficients are from the IV model described in Section 4.3. Marital status-dependent variables are denoted at the top of each column. All specifications use the wild cluster bootstrap procedure with 1000 replications to estimate *p*-values, as proposed by Cameron et al. (2008). Wild cluster bootstrap *p*-values are shown in brackets.

***$p < .01$, **$p < .05$, *$p < .10$.

Source: American Community Survey 1-year Public Use Microdata Sample files, 2008–2019.

among the low educated sample (Panel B). Interestingly, under this specification, the full sample coefficients for marriage and divorce flow are each significant at the 5% level. For flow outcomes, there is hardly any difference between the coefficients for the full and low education samples (for marriage flow, the low education coefficient is slightly more imprecisely estimated). Overall, Table 7 shows that marriage and divorce stock results are robust to an alternative specification, and additionally marriage flow is negative and significant, while divorce flow is positive and significant.

Table 8 presents results comparing effects in new expander states to two different control group definitions: (1) 12 never-expander states and 30 earlier/later expanders; and (2) only the 30 earlier/later expanders. The results in Table 8 provide further evidence that the effects of Medicaid expansion on marital outcomes appear to be robust to the choice of control group. Coefficients on marriage stock are negative and significant at the highest level, and those for divorce stock remain positive and significant. Additionally, marriage flow effects are negative and significant under each specification. While being positive in sign, divorce flow estimates remain insignificant under each specification. Once again, we believe that these additional models lend support to the main findings, particularly showing robustness of the marriage and divorce stock effects.

TABLE 7 The effects of Medicaid expansion on marital status: Generalized DD model

	Marriage stock (1)	Divorce stock (2)	Marriage flow (3)	Divorce flow (4)
Panel A: Full sample				
DD effect	−.0070***	.0045***	−.0007**	.0006***
	[.000]	[.000]	[.027]	[.003]
Sample mean	0.7844	0.1587	0.0312	0.0146
Observations	15,612,089	15,612,089	15,612,089	15,612,089
Panel B: Low education				
DD effect	−.0080***	.0054***	−.0007	.0006***
	[.001]	[.001]	[.102]	[.003]
Sample mean	0.7367	0.1817	0.0280	0.0157
Observations	5,618,982	5,618,982	5,618,982	5,618,982

Note: Sample includes all individuals aged 18–64 years (Panel A) and all individuals aged 18–64 years with a high school degree or less (Panel B). Estimated coefficients are from the generalized DD model described in Section 4.3. Marital status-dependent variables are denoted at the top of each column. All specifications use the wild cluster bootstrap procedure with 1000 replications to estimate *p*-values, as proposed by Cameron et al. (2008). Wild cluster bootstrap *p*-values are shown in brackets.

Abbreviation: DD, difference-in-differences.

***$p < .01$, **$p < .05$.

Source: American Community Survey 1-year Public Use Microdata Sample files, 2008–2019.

TABLE 8 The effects of Medicaid expansion on marital status

	Marriage stock (1)	Divorce stock (2)	Marriage flow (3)	Divorce flow (4)
Panel A: Control group = 12 never expanders and 30 earlier/later expanders				
DD effect	−.0088***	.0054***	−.0010*	.0003
	[.000]	[.002]	[.052]	[.138]
Observations	15,612,089	15,612,089	15,612,089	15,612,089
Panel B: Control group = 30 earlier/later expanders				
DD effect	−.0090***	.0060***	−.0012***	.0003
	[.002]	[.002]	[.003]	[.136]
Observations	11,000,241	11,000,241	11,000,241	11,000,241

Note: Sample includes all individuals aged 18–64 years. Both panels present estimates from the DD model outlined by Equation (1) using alternative control groups. Marital status-dependent variables are denoted at the top of each column. All specifications use the wild cluster bootstrap procedure with 1000 replications to estimate *p*-values, as proposed by Cameron et al. (2008). Wild cluster bootstrap *p*-values are shown in brackets.

Abbreviation: DD, difference-in-differences.

***$p < .01$, *$p < .10$.

Source: American Community Survey 1-year Public Use Microdata Sample files, 2008–2019.

5.4.2 | Placebo analyses

Table 9 presents estimates obtained from our rolling window placebo analysis following Slusky (2017). We choose four different 5-year windows (2011–2015, 2010–2014, 2009–2013, and 2008–2012) and impose artificial Medicaid expansions in the nine new expander states in the years 2013, 2012, 2011, and 2010, respectively. We present estimates of stock outcomes for the full sample (Panel A) and those with low education (Panel B). From the table, of the 16 marriage and

TABLE 9 Rolling window artificial treatment effects

	Full sample		Low education	
	Marriage stock (1)	**Divorce stock (2)**	**Marriage stock (3)**	**Divorce stock (4)**
Panel A: 2011–2015 (Treatment in 2013)				
DD effect	−.0020	.0003	−.0012	.0003
	[.265]	[.831]	[.994]	[.884]
Observations	2,703,297	2,703,297	1,056,888	1,056,888
Panel B: 2010–2014 (Treatment in 2012)				
DD effect	−.0008	.0014	.0004	.0014
	[.681]	[.286]	[.852]	[.519]
Observations	2,725,625	2,725,625	1,076,008	1,076,008
Panel C: 2009–2013 (Treatment in 2011)				
DD effect	−.0019	.0025*	−.0015	.0023
	[.209]	[.075]	[.608]	[.337]
Observations	2,750,246	2,750,246	1,093,268	1,093,268
Panel D: 2008–2012 (Treatment in 2010)				
DD effect	−.0022	.0020	−.0034	.0028
	[.226]	[.153]	[.280]	[.372]
Observations	2,767,728	2,767,728	1,107,332	1,107,332

Note: Sample includes all individuals aged 18–64 years. Estimated coefficients are from the DD model outlined by Equation (1) using rolling window artificial treatment effects following Slusky (2017). All specifications use the wild cluster bootstrap procedure with 1000 replications to estimate *p*-values, as proposed by Cameron et al. (2008). Wild cluster bootstrap *p*-values are shown in brackets.

Abbreviation: DD, difference-in-differences.

*$p < .10$.

Source: American Community Survey 1-year Public Use Microdata Sample files, 2008–2015.

divorce stock estimates, all but one are statistically insignificant. Only one of the estimates (divorce stock among the full sample in Panel C) is significant, and only at the 10% level. Overall, the fact that these artificial treatment effects are statistically indistinguishable from zero lends further evidence that our main estimates are a reflection of the 2014 Medicaid expansion and are not spuriously driven by other factors differentially impacting the treatment and control states.

Finally, Table 10 presents estimates from an additional placebo test capturing the impact of Medicaid expansion on marital outcomes of the elderly (aged 65 and up). Given that individuals aged 65 and above qualify for Medicare, it appears unlikely that Medicaid policy changes would impact marital decisions within this group. Table 10 confirms that there are no significant effects of Medicaid policy on the marital decisions of the elderly. This finding (or lack thereof) further indicates that our main estimates are not spuriously driven by other changes that occurred during the sample period.

5.4.3 | Estimates using CPS and PSID data

To provide evidence that the results are robust to the choice of dataset, we replicate our analysis using data from the two other representative samples: the CPS and the PSID. While these additional datasets do not contain information on flow outcomes, we are able to estimate the effects on the stock of married and divorced individuals. The DD results for the CPS and PSID analysis are presented in Table 11. Consistent with our ACS estimates, we find that Medicaid expansion led to a statistically significant reduction in marriage stock among individuals in treated states. While again finding a positive effect on the likelihood of being divorced in both additional datasets, these estimates are imprecisely estimated.

TABLE 10 Placebo test (above the age of 65 years)

	Marriage stock (1)	Divorce stock (2)	Marriage flow (3)	Divorce flow (4)
Panel A: Full sample				
DD effect	−.0024	.0008	.0001	.0001
	[.386]	[.327]	[.621]	[.335]
Sample mean	0.5864	0.1140	0.0023	0.0029
Observations	2,745,406	2,745,406	2,745,406	2,745,406
Panel B: Low education				
DD effect	−.0008	−.0005	.0000	.0001
	[.753]	[.607]	[.984]	[.329]
Sample mean	0.5412	0.1066	0.0020	0.0030
Observations	1,442,527	1,442,527	1,442,527	1,442,527

Note: Sample includes all individuals aged 65 years and up (Panel A) and all individuals aged 65 years and up with a high school degree or less (Panel B). Estimated coefficients are from the DD model outlined in Equation (1). Marital status-dependent variables are denoted at the top of each column. All specifications use the wild cluster bootstrap procedure with 1000 replications to estimate *p*-values, as proposed by Cameron et al. (2008). Wild cluster bootstrap *p*-values are shown in brackets.

Abbreviation: DD, difference-in-differences.

Source: American Community Survey 1-year Public Use Microdata Sample files, 2008–2019.

TABLE 11 The effects of Medicaid expansion on marriage—Alternative datasets

	Full sample		Low education	
	Marriage stock (1)	Divorce stock (2)	Marriage stock (3)	Divorce stock (4)
Panel A: CPS IPUMS				
DD effect	−.0136***	.0032	−.0226***	.0058
	[.003]	[.109]	[.002]	[.107]
Sample mean	0.5708	0.1156	0.5145	0.1237
Observations	738,240	738,240	313,611	313,611
Panel B: PSID				
DD effect	−.0239**	.0114	.0261**	.0142
	[.011]	[.390]	[.043]	[.391]
Sample mean	0.5268	0.1786	0.4776	0.1979
Observations	70,441	70,441	32,842	32,842

Note: Sample includes all individuals aged 18–64 years (columns 1 and 2) and all individuals aged 18–64 years with a high school degree or less (columns 3 and 4). Estimated coefficients are from the DD model outlined in Equation (1). Marital status-dependent variables are denoted at the top of each column. All specifications use the wild cluster bootstrap procedure with 1000 replications to estimate *p*-values, as proposed by Cameron et al. (2008). Wild cluster bootstrap *p*-values are shown in brackets.

Abbreviations: CPS, Current Population Survey; DD, difference-in-differences; IPUMS, Integrated Public Use Microdata Series; PSID, Panel Study of Income Dynamics.

$^{***}p < .01$, $^{**}p < .05$.

Source: IPUMS Current Population Survey, 2008–2019, and Panel Study of Income Dynamics, 2009–2019.

Table 11 furthermore shows that the treatment effects are larger in magnitude among lower-educated individuals, which is again in line with our ACS analysis. The consistency in the findings across all three datasets lends evidence that the ACS results are externally valid.

6 | DISCUSSION AND CONCLUSIONS

Our analysis indicates that the 2014 ACA Medicaid expansions led to statistically significant changes in marriage and divorce stock among individuals living in new expansion states, relative to states that have never expanded their Medicaid programs. Analyzing ACS data from 2008-2019, we find that the 2014 expansions decreased the likelihood that individuals are currently married by 0.95%, and increased the likelihood of being currently divorced by 2.22%. We find that effects are particularly pronounced among the low educated, a subgroup likely to be impacted by Medicaid policy. To show robustness of the main findings, we test for effects across multiple control group definitions. Additionally, we conduct placebo analyses in which we show that there are no significant effects of four artificial Medicaid expansions, and no effects among those aged 65 and older, a group that should remain largely unaffected by Medicaid policy. We validate our marriage stock findings using data from both the CPS and the PSID.

The estimated reduction in marriage among working-aged adults is smaller in magnitude than findings of Abramowitz (2016), who estimates reductions in marriage flow to the order of 9% following implementation of the ACA young adult provision. While our marriage and divorce flow estimates are less consistent than our findings for stock outcomes, under some specifications we find significant changes in the flow of newly married/divorced following the change in policy. Overall, our stock findings are consistent with the proposition that insurance options influence the marriage decisions of individuals, and Medicaid expansion offers an alternative avenue to obtain insurance outside of spousal coverage.

Hampton and Lenhart (2019) find that the ACA preexisting conditions provision reduced reliance on spousal health insurance among people with health conditions. While it is likely that the ACA Medicaid expansions also decreased reliance on spousal coverage, it is important to reiterate that the marriage mechanism driving these results is twofold. First, following expansion of a state's Medicaid program, a single individual may now qualify for Medicaid, whereas previously he or she could not. This reduces dependence on spousal health insurance coverage. Second, expansions of Medicaid programs may encourage couples to strategically divorce (or forego marriage) so that individual incomes fall below the Medicaid eligibility threshold.

Given that the primary purpose of Medicaid is to provide insurance to those who cannot afford private coverage, the potential for strategic divorcing should be of concern to state policymakers as they make further decisions regarding their programs. Another concern, and one that has been largely overlooked over time in the United States, is the link between insurance coverage and incentives to marry. It appears likely that this link has led to distortions in the marriage market, leading some people to marry for the wrong reasons. Similar to job lock being an inefficiency in the labor market, policymakers should view marriage lock as an analogous inefficiency and consider policies that improve the insurance options of individuals. If individuals are altering marriage decisions following Medicaid expansion, policymakers should be concerned in a crowding-out of private coverage. At the same time, however, policymakers should be made aware of any mechanism that may provide incentives for people to alter their major life decisions such as marriage.

ORCID

Otto Lenhart https://orcid.org/0000-0003-0949-4820

ENDNOTES

[1] As an additional measure of marriage flow, the American Community Survey (ACS) also contains information on the year an individual was last married. Using this survey question to construct a measure of married flow yields qualitatively similar results.

[2] Table A1 displays descriptive statistics of the additional IPUMS Current Population Survey and Panel Study of Income Dynamics samples.

[3] In his influential work, Goodman-Bacon (2020) shows that two-way fixed effects difference-in-differences (DD) coefficients provide weighted averages of all possible simple 2 × 2 DDs that compare one group that changes treatment status to another group that does not. He points out that the use of previously treated units as controls requires an additional identifying assumption of time-invariant treatment effects. In additional robustness check specifications in the later part of the paper, we expand our definition of the control group.

[4] In 2013, the ACS changed the coding of same-sex married couples from "unmarried partners" to be the same as all married couples. Our results are not sensitive to changes in the coding of same-sex couples.

[5] As an alternative specification, we follow Akosa Antwi et al. (2013) and separate the treatment into early (2014–2016) and late (2017–2019) effects. We present results for this alternative specification in Table A2.

[6] The results are robust to the exclusion of the wild bootstrap resampling. In additional variations to the standard DD model, we also estimate propensity score matching DD models as well as an alternative DD model introduced by Mora and Reggio (2015), which

identifies the effect of the policy using a fully flexible dynamic specification and includes a family of alternative parallel growth assumptions. The main DD results are robust to these additional specifications.

[7] The noticeable decrease in Medicaid coverage in 2019 (in both new expander and never expanding states) is likely due to the repeal of the Shared Responsibility Payment of the ACA, which became effective on December 31, 2018.

[8] We can compare the magnitude of the first-stage effect with other recent studies of Medicaid expansion and insurance coverage. Leung and Mas (2016) find that ACA Medicaid expansion is associated with a 34.88% increase in Medicaid coverage among childless adults, while Kaestner et al. (2017) estimate increases in Medicaid coverage to the order of 50%.

[9] To check whether the event study estimates in Table 2 are influenced by multiple hypothesis testing, we estimated additional specifications that use the Romano-Wolf stepdown procedure to account for the probability of making any type I errors by accounting for the dependence among the *p*-values by bootstrap resampling. We find that the event study effects remain almost unchanged when accounting for the role of multiple hypothesis testing, suggesting that the estimates in Table 2 are not the result of multiple hypothesis testing.

[10] While the main analysis includes all individuals aged 18–64 years, to mitigate concerns that policy effects are driven by the Dependent Coverage Provision, Table A3 shows estimates limiting the age of the sample to 26–64. Results comparing this restricted age sample to the full sample are qualitatively similar.

[11] Slusky and Ginther (2021) state that due to the anticipatory nature of marriage as an outcome variable, it is ambiguous whether the years 2012 and 2013 are treated or not. Following their approach, we estimate additional models that drop these years from the analysis. Results for this alternative specification are presented in Table A4.

[12] Along the lines of the heterogeneity studied in Slusky and Ginther (2021), we additionally estimate models testing for heterogeneous policy effects across gender and race. These additional results are included in Table A5.

REFERENCES

Abramowitz, J. (2016) Saying "I Don't": the effect of the Affordable Care Act young adult provision on marriage. *Journal of Human Resources*, 51(4), 933–960.

Abramowitz, J. & Dillender, M. (2017) *Considering the use of stock and flow outcomes in empirical analyses: an examination of marriage data*. Working Papers 17-64. Center for Economic Studies, U.S. Census Bureau.

Alm, J. & Whittington, L.A. (1997) Income taxes and the timing of marital decisions. *Journal of Public Economics*, 64(2), 219–240.

Alm, J. & Whittington, L.A. (1999) For love or money? The impact of income taxes on marriage. *Economica*, 66(263), 297–316.

Antwi, A., Yaa, A.S.M. & Simon, K. (2013) Effects of federal policy to insure young adults: evidence from the 2010 Affordable Care Act's dependent-coverage mandate. *American Economic Journal: Economic Policy*, 5(4), 1–28.

Berchick, E.R., Hood, E. & Barnett, J.C. (2018) *Health insurance coverage in the United States: 2017. Current Population Reports*. Washington: US Government Printing Office, 60-264.

Borgschulte, M. & Vogler, J. (2020) Did the ACA Medicaid expansion save lives? *Journal of Health Economics*, 72, 1023333.

Buchmueller, T.C., Levy, H.G. & Valletta, R.G. (2019) *Medicaid expansion and the unemployed*. No. w26553. National Bureau of Economic Research.

Bullinger, L.R. (2021) Child support and the Affordable Care Act's Medicaid expansions. *Journal of Policy Analysis and Management*, 40(1), 42–77.

Cameron, A.C., Gelbach, J.B. & Miller, D.L. (2008) Bootstrap-based improvements for inference with clustered errors. *The Review of Economics and Statistics*, 90(3), 414–427.

Chen, T. (2019). *Health insurance coverage and marriage behavior: is there evidence of marriage lock?* No. 2019-09. University of Connecticut, Department of Economics.

Courtemanche, C., Marton, J., Ukert, B., Yelowitz, A. & Zapata, D. (2017) Early impacts of the Affordable Care Act on health insurance coverage in Medicaid expansion and non-expansion states. *Journal of Policy Analysis and Management*, 36(1), 178–210.

Courtemanche, C.J., Marton, J. & Yelowitz, A. (2019) *Medicaid coverage across the income distribution under the Affordable Care Act*. No. w26145. National Bureau of Economic Research.

Cowan, B.W. & Hao, Z. (2021) Medicaid expansions and the mental health of college students. *Health Economics*, 30(6), 1306–1327.

Fronstin, P. & Roebuck, M.C. (2014) The cost of spousal health coverage. *Employee Benefit Research Institute Notes*, 35(1), 2–7.

Goodman-Bacon, A.J. (2020) Difference-in-differences with variation in treatment timing. *NBER Working Paper No. 25018*. Available from: http://goodman-bacon.com/pdfs/ddtiming.pdf [Accessed 14th March 2021].

Hampton, M. & Lenhart, O. (2019) The effect of the Affordable Care Act preexisting conditions provision on marriage. *Health Economics*, 28(11), 1345–1355.

Hampton, M. & Lenhart, O. (2021) *Access to health care and mental health–evidence from the ACA preexisting conditions provision*. Available from: https://ssrn.com/abstract=3770085

Hancock, J. (2013) UPS won't insure spouses of many employees. *USA Today/Kaiser Health News*. Available from: http://www.usatoday.com/story/money/business/2013/08/20/ups-spouses-health-insurance/2651713/ [Accessed 18th September 2019].

Kaestner, R., Garrett, B., Chen, J., Gangopadhyaya, A. & Fleming, C. (2017) Effects of ACA Medicaid expansions on health insurance coverage and labor supply. *Journal of Policy Analysis and Management*, 36(3), 608–642.

Kaiser Family Foundation. (2019) *Employer-sponsored coverage rates for the nonelderly by age. State Health Facts*. Available from: https://www.kff.org/other/state-indicator/rate-by-age-2/?currentTimeframe=0&sortModel=%7B%22colId%22:%22Location%22,%22sort%22:%22asc%22%7D [Accessed 28th October 2020].
Klerman, J.A. & Haider, S.J. (2004) A stock-flow analysis of the welfare caseload. *Journal of Human Resources*, 29(4), 865–886.
Leung, P. & Mas, A. (2016) *Employment effects of the ACA Medicaid expansions*. No. w22540. National Bureau of Economic Research.
Miller, S., Johnson, N. & Wherry, L.R. (2019) Medicaid and mortality: new evidence from linked survey and administrative data. *NBER Working Paper No. 26081*. Available from: https://www.nber.org/papers/w26081 [Accessed 20th February 2021].
Moffitt, R. (1990) The effect of the US welfare system on marital status. *Journal of Public Economics*, 41(1), 101–124.
Mora, R. & Reggio, I. (2015) Didq: a command for treatment-effect estimation under alternative assumption. *Stata Journal*, 15(3), 796–808.
Peng, L., Guo, X. & Meyerhoefer, C.D. (2020) The effects of Medicaid expansion on labor market outcomes: evidence from border counties. *Health Economics*, 29(3), 245–260.
Slusky, D.J.G. (2017) Significant placebo results in difference-in-differences analysis: the case of the ACA's parental mandate. *Eastern Economic Journal*, 43(4), 580–603.
Slusky, D.J.G. & Ginther, D.K. (2021) Did Medicaid expansion reduce medical divorce? *Review of Economics of the Household*, 19, 1139–1174.
Yelowitz, A.S. (1998) Will extending Medicaid to two-parent families encourage marriage? *Journal of Human Resources*, 33(4), 833–865.

SUPPORTING INFORMATION

Additional supporting information may be found in the online version of the article at the publisher's website.

How to cite this article: Hampton, M. & Lenhart, O. (2021) The effect of the Affordable Care Act Medicaid expansion on marriage. *Economic Inquiry*, 1–24. Available from: https://doi.org/10.1111/ecin.13052

APPENDIX

TABLE A1 Descriptive statistics

	CPS		PSID	
	New expanders	**Never expanders**	**New expanders**	**Never expanders**
Married				
Pre	0.5708	0.5695	0.5268	0.4807
Post	0.5363	0.5507	0.5190	0.5089
Divorced				
Pre	0.1156	0.1069	0.1307	0.1329
Post	0.1167	0.1028	0.1279	0.1250
Age	40.8881	40.6031	38.5623	38.8111
Male	0.4838	0.4806	0.6973	0.6770
White	0.8449	0.7848	0.6262	0.4384
Black	0.0834	0.1457	0.3481	0.5159
Other race	0.0717	0.0695	0.0257	0.0457
High school degree or less	0.4295	0.4210	0.4840	0.4619
At least some college	0.5705	0.5790	0.5160	0.5381
Unemployment rate	6.6440	6.1082	7.6576	6.8994
Observations	202,445	599,123	16,027	54,414

Note: Sample means for new expander and never-expander states. Sample includes all individuals aged 18–64 years.

Abbreviations: CPS, Current Population Survey; IPUMS, Integrated Public Use Microdata Series; PSID, Panel Study of Income Dynamics.

Source: IPUMS Current Population Survey, 2008–2019 and Panel Study of Income Dynamics, 2009–2019.

TABLE A2 Early and late treatment effects

	Marriage stock (1)	Divorce stock (2)	Marriage flow (3)	Divorce flow (4)
Panel A: Full sample				
Treatment in 2014–2016	−.0044	.0025	−.0010**	.0006*
	[.108]	[.183]	[.015]	[.052]
Treatment 2017 and later	−.0105***	.0054**	−.0000	.0005
	[.000]	[.010]	[.993]	[.102]
Observations	6,523,901	6,523,901	6,523,901	6,523,901
Panel B: Low education				
Treatment in 2014–2016	−.0084**	.0056*	−.0005	.0006
	[.041]	[.052]	[.496]	[.138]
Treatment 2017 and later	−.0143***	.0076**	.0005	.0008
	[.000]	[.012]	[.578]	[.114]
Observations	2,499,017	2,499,017	2,499,017	2,499,017

Note: Sample includes all individuals aged 18–64 years (Panel A) and all individuals aged 18–64 years with a high school degree or less (Panel B). Estimated coefficients are from the alternative DD specification following Akosa Antwi et al. (2013). Marital status-dependent variables are denoted at the top of each column. All specifications use the wild cluster bootstrap procedure with 1000 replications to estimate *p*-values, as proposed by Cameron et al. (2008). Wild cluster bootstrap *p*-values are shown in brackets.

Abbreviation: DD, difference-in-differences.

***$p < .01$, **$p < .05$, *$p < .10$.

Source: American Community Survey 1-year Public Use Microdata Sample files, 2008–2019.

TABLE A3 The effects of Medicaid expansion on outcomes (aged 26–64 years)

	Medicaid coverage (1)	Marriage stock (2)	Divorce stock (3)
Panel A: Full sample			
DD effect	.0379***	−.0074**	.0040**
	[.000]	[.011]	[.038]
Sample mean	0.1345	0.7673	0.1790
Observations	6,318,651	6,318,651	6,318,651
Panel B: Low education			
DD effect	.0596***	−.0115***	.0070**
	[.000]	[.003]	[.014]
Sample mean	0.1937	0.7233	0.2036
Observations	2,405,480	2,405,480	2,405,480
Panel C: High education			
DD effect	.0244***	−.0047**	.0025*
	[.000]	[.016]	[.064]

TABLE A3 (Continued)

	Medicaid coverage (1)	Marriage stock (2)	Divorce stock (3)
Sample mean	0.0930	0.7980	0.1617
Observations	3,913,171	3,913,171	3,913,171

Note: Sample includes all individuals aged 26–64 years (Panel A) and all individuals aged 26–64 years with a high school degree or less (Panel B). Estimated coefficients are from the DD model outlined by Equation (1). Medicaid coverage and marital status-dependent variables are denoted at the top of each column. All specifications use the wild cluster bootstrap procedure with 1000 replications to estimate *p*-values, as proposed by Cameron et al. (2008). Wild cluster bootstrap *p*-values are shown in brackets.

Abbreviation: DD, difference-in-differences.

***$p < .01$, **$p < .05$, *$p < .10$.

Source: American Community Survey one-year Public Use Microdata Sample files, 2008–2019.

TABLE A4 The effects of Medicaid expansion on marital status (2012 and 2013 are omitted)

	Marriage stock (1)	Divorce stock (2)	Marriage flow (3)	Divorce flow (4)
Panel A: Full sample				
DD effect	−.0080**	.0047**	−.0006	.0006
	[.014]	[.029]	[.234]	[.0003]
Sample mean	0.7740	0.1730	0.0288	0.0166
Observations	5,436,757	5,436,757	5,436,757	5,436,757
Panel B: Low education				
DD effect	−.0119**	.0073**	.0003	.0008*
	[.010]	[.025]	[.667]	[.094]
Sample mean	0.7316	0.1965	0.0262	0.0176
Observations	2,073,977	2,073,977	2,073,977	2,073,977

Note: Sample includes all individuals aged 18–64 years (Panel A) and all individuals aged 18–64 years with a high school degree or less (Panel B). Estimated coefficients are from the DD model outlined by Equation (1). Marital status-dependent variables are denoted at the top of each column. All specifications use the wild cluster bootstrap procedure with 1000 replications to estimate *p*-values, as proposed by Cameron et al. (2008). Wild cluster bootstrap *p*-values are shown in brackets.

Abbreviation: DD, difference-in-differences.

**$p < .05$, *$p < .10$.

Source: American Community Survey 1-year Public Use Microdata Sample files, 2008–2019 (2012 and 2013 are omitted).

TABLE A5 The effects of Medicaid expansion, by gender and race

	Male (1)	Female (2)	Black (3)	White (4)	Other race (5)
Panel A: Medicaid coverage					
DD effect	.0324***	.0433***	.0527***	.0377***	.0444***
	[.000]	[.000]	[.000]	[.000]	[.000]
Sample mean	0.1435	0.1289	0.2571	0.1272	0.1439
Observations	3,052,383	3,471,518	662,808	5,339,328	521,765
Panel B: Marriage stock					
DD effect	−.0088***	−.0058*	−.0012	−.0089***	.0078**
	[.000]	[.053]	[.863]	[.001]	[.013]

(Continues)

TABLE A5 (Continued)

	Male (1)	Female (2)	Black (3)	White (4)	Other race (5)
Sample mean	0.7938	0.7494	0.5801	0.7822	0.7805
Observations	3,052,383	3,471,518	662,808	5,339,328	521,765
Panel C: Divorce stock					
DD effect	.0062***	.0017	−.0019	.0062***	−.0095**
	[.001]	[.391]	[.734]	[.000]	[.010]
Sample mean	0.1695	0.1818	0.2807	0.1703	0.1578
Observations	3,052,383	3,471,518	662,808	5,339,328	521,765

Note: Sample includes all individuals aged 18–64 years. Estimated coefficients are from the DD model outlined by Equation (1). Subgroup regressions are denoted at the top of each column. All specifications use the wild cluster bootstrap procedure with 1000 replications to estimate *p*-values, as proposed by Cameron et al. (2008). Wild cluster bootstrap *p*-values are shown in brackets.

Abbreviation: DD, difference-in-differences.

$^{***}p < .01$, $^{**}p < .05$, $^{*}p < .10$.

Source: American Community Survey 1-year Public Use Microdata Sample files, 2008–2019.