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Health Insurance Mandates and the Marriage of Young Adults: A Comment on Barkowski and McLaughlin

Aaron M. Gamino[1]

LINK TO ABSTRACT

In the United States, the most common form of health insurance coverage is through employer-sponsored insurance (ESI) plans. ESI plans cover the workers and their dependents—typically the spouse and children. As a means of increasing young-adult insurance coverage, states and the federal government have enacted "dependent" mandates that expand the definition of a dependent for ESI plans. At the federal level, the Affordable Care Act (ACA) dependent mandate increased the maximum age of an adult child dependent from 18 to 25. In addition to the federal expansion, the majority of states enacted dependent mandates which extended dependent status to children over the age of 18. State mandates commonly required that to be eligible the adult child must be unmarried or a student.

Scott Barkowski and Joanne Song McLaughlin (2022) explore the impact of dependent mandates and their restrictions on the marriage outcomes of targeted young adults. To do so, they use variation in dependent mandate timing and eligibility at both the federal and state (including the District of Columbia) levels. Barkowski and McLaughlin's identification strategy hinges on a parallel-trends assumption. Their main model assumes that changes in marriage rates for younger persons affected by state and ACA dependent coverage mandates are the same as those for older persons unaffected. Importantly, treatment is defined by age, state,

1. Middle Tennessee State University, Murfreesboro, TN 37132.

and year because different states have different age thresholds. This necessitates the inclusion of age-by-year, state-by-year, and age-by-state fixed effects to isolate the policy's impact. Age-by-year fixed effects are excluded in all the authors' models, which leads to the estimates of interest unintentionally capturing age-by-year differences.

In this comment, I summarize the empirical strategy Barkowski and McLaughlin (2022) employed and outline how omitting controls for the interactions of age, year, and state may result in biased estimates. I replicate their findings and estimate the model with the proper set of controls. When the model is correctly specified, I find that the results in Barkowski and McLaughlin (2022) are not statistically significant and, in the case of the likelihood of being married, the signs change, and the estimates are smaller. I perform additional analyses that demonstrate the main regression model specification cannot identify changes in ESI coverage and fails to find support that marriage acts as a mediator of the federal mandate's impact on ESI coverage.

Barkowski and McLaughlin's empirical strategy and findings

To assess the impact of dependent mandates on marriage outcomes, Barkowski and McLaughlin (2022) use a sample of young adults aged 19 to 25 from the IPUMS-USA 2000–2015 American Community Survey (ACS), along with their novel legal data. The primary outcome of interest is whether a young adult is married at the interview date. They use the following difference-in-differences (DD) model (Equation 5 in their paper):

$$Y_{iast} = \beta_1 ELIG_{ast} \times ACA_t + \beta_2 ELIG_{ast} + X'_{iast}\gamma + a_a + \delta_{st} + u_{iast}, \tag{1}$$

where i, a, s, and t index individual, age in years, state, and time in years, respectively. $ELIG_{ast}$ is an indicator taking a value of one for individuals who are currently age-eligible for state dependent mandates. ACA_t is an indicator taking a value of one after the ACA dependent mandate went into effect—2011 and onward. X'_{iast} is a vector of controls for race, Hispanic ethnicity, gender, the interaction of age and gender, the unemployment rate, and the male population ratio. Lastly, a_a and δ_{st} are single-year of age and state-by-time fixed effects. Barkowski and McLaughlin use the ACS person weights and cluster standard errors by state.

The two coefficients of interest are β_1 and β_2. Barkowski and McLaughlin find β_2 to be negatively signed and significant and interpret this as implying eligible individuals were less likely to be married than ineligible individuals. β_1 is positively signed and statistically significant. The authors interpret this result as signifying a reduction in the difference in the likelihood of marriage across eligible and ineligible individuals. The magnitude of their estimate for β_1 range from 4.6 to 30.4 percent of the sample mean, and the magnitude of their estimates for β_2 range from 4.9 to 13.3 percent of the sample mean.

The authors examine marriage flows using a sample consisting of 23- to 25-year-olds and 27- to 30-year-olds. The marriage entry sample is limited to individuals who married in the last year and individuals who are currently unmarried but were not divorced or were widowed in the last year. The marriage exit sample is limited to individuals who divorced or widowed in the last year and individuals who are currently married. The age and year variables are shifted back by a year to reflect conditions at the start of the reference period. For marriage flows, they use the following model (Equation 6 in their paper):

$$Z_{iast} = \beta_1 ELIG_{ast} \times ACA_t + \beta_2 ELIG_{ast} + \beta_3 ELIG_{ast} \times ACA_t \times OV26_a + \beta_4 ACA_t \times OV26_a + \beta_5 ELIG_{ast} \times OV26_a + X'_{iast}\gamma + a_a + \delta_{st} + u_{iast}. \quad (2)$$

This model follows the same notation as Equation 1. Z_{iast} is the marriage flow outcome and $OV26_a$ is an indicator for individuals over 26 years of age. The authors find positive and significant effects for β_1 and negative and mostly significant effects for β_2, which the authors interpret in the same fashion as before. The authors find a reduction in marriage entry for individuals under 26 that are ineligible for state mandates and an increase in marriage entry for individuals under 26 that were eligible for state mandates.

Problems with Barkowski and McLaughlin's models

The models employed by Barkowski and McLaughlin (2022) are potentially misspecified difference-in-difference-in-differences (DDD) models. The models omit relevant interaction terms. $ELIG_{ast}$ varies across three dimensions—age, state, and year—which requires the inclusion of three sets of two-way interaction terms: state-by-year, age-by-state, and age-by-year fixed effects. Barkowski and McLaughlin estimate models with various combinations of these two-way interactions included but did not estimate models with all three. Specifically, age-by-year effects are never included.

Barkowski and McLaughlin (2022) justify using a DD model in their primary specification (Equation 5 in their paper), despite the entire sample of 19- to 25-year-olds being treated by the ACA, because the authors predict oppositely signed effects from the ACA mandate for those eligible and ineligible for state mandates. Barkowski and McLaughlin note that $ELIG_{ast}$ varies across three dimensions but point out that there is no clear prediction for the ACA mandate from a DDD style specification. They argue that the DD approach employed implies that the identification of β_1 and β_2 comes from within-state variation. The authors claim that age-by-year interaction fixed effects are excluded because that would imply identification across states, which they say is less desirable than identification from within-state variation (Barkowski and McLaughlin 2022, 645).

The argument made for using a DD model by Barkowski and McLaughlin (2022) conflicts with the argument made in a related paper by Barkowski, McLaughlin, and Ray (2020), which uses the same variation in a DDD model to identify the impact of mandates on insurance coverage. Barkowski, McLaughlin, and Ray (2020, 1640) note that $ELIG_{ast}$ varies across three dimensions, which necessitates the inclusion of age-by-state, age-by-time, and state-by-time fixed effects—denoted as γ_{as}, δ_{at}, and μ_{st}, respectively—to correctly identify the effect. This argument contrasts with Barkowski and McLaughlin (2022), where the authors make the case that the exclusion of age-by-year fixed effects is preferred.

Proper identification of state mandate eligibility's effect on the likelihood of marriage is essential for interpreting both terms of interest in Barkowski and McLaughlin (2022). It is not immediately apparent how the absence of age-by-year (and age-by-state in some specifications) fixed effects affect the base model's performance. The age-by-year fixed effects alone number over 100 and account for almost 18 percent of the variation in $ELIG_{ast}$.

Replication and a corrected model

I begin by replicating Barkowski and McLaughlin's main results, reported in columns 1–4 of Table 4 in their article (2022, 672). I follow the original analysis and use a sample of young adults aged 19 to 25 from the IPUMS-USA 2000–2015 ACS samples. I use the policy data provided in the replication files to generate the $ELIG_{ast}$ term.

In Table 1, I present the results from my replication of Barkowski and McLaughlin's (2022, 672) Table 4, and the results from a model that included the full set of two-way interactions. I report the coefficients and standard errors. Columns 1–4 correspond to columns 1–4 in Barkowski and McLaughlin's Table 4, while column 5 does not. In column 5, I report results from the following DDD model:

$$Y_{iast} = \beta_1 ELIG_{ast} \times ACA_t + \beta_2 ELIG_{ast} + X'_{iast}\gamma + a_a + \delta_{st} + \theta_{as} + \pi_{at} + u_{iast}. \quad (3)$$

Equation 3 follows Equation 1 but includes the additional two-way interaction terms θ_{as} and π_{at} which are vectors containing age-by-state and age-by-time fixed effects. When the full set of two-way interactions are included, $ELIG_{ast}$ captures the triple interaction. I closely replicated the results in Barkowski and McLaughlin (2022); the coefficients and standard errors are identical when rounded to the thousandth digit. All but one estimate in both the original and replication are statistically significant at conventional levels.

In column 5, the results from a corrected model are reported. When the model includes state-by-year, age-by-state, and age-by-year fixed effects, the estimated effect of the state mandates and interaction of the state mandates and ACA mandate is very small—virtually zero—and insignificant. In an exercise in Appendix A, I demonstrate that the relevant omitted interaction terms are unintentionally being picked up in the coefficients of interest in Barkowski and McLaughlin (2022), leading to large effects for completely random policies and severe over-rejection rates of the null hypothesis in t-tests (roughly 64 percent of the placebo coefficients are found to be significant).

TABLE 1. Estimates of state and federal mandate interaction effects on marriage

	(1)	(2)	(3)	(4)	(5)
Eligible under state mandates × ACA	0.00744** (0.00365)	0.0117** (0.00442)	0.0302*** (0.00589)	0.0485*** (0.00567)	−0.0030 (0.00437)
Eligible under state mandates	−0.00775** (0.00376)	−0.0103** (0.00421)	−0.0210*** (0.00757)	−0.0101 (0.0110)	0.0003 (0.00408)
Corresponding result in Barkowski and McLaughlin (2022, 672)	Table 4, Column 1	Table 4, Column 2	Table 4, Column 3	Table 4, Column 4	n/a
Linear state trend	Yes	Yes	No	No	No
Quadratic state trend	No	Yes	No	No	No
State-year FE	No	No	Yes	Yes	Yes
Age-state FE	No	No	No	Yes	Yes
Age-year FE	No	No	No	No	Yes
Observations = 3,199,012					

Notes: Estimated coefficients and standard errors (in parenthesis) are reported. Columns 1–4 are replications of the results in Barkowski and McLaughlin's Table 4 (2022, 672). Column 5 is the specification including the full set of two-way interactions. All regressions were performed using ACS person weights with standard errors clustered by state. *, **, and *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively.

Next, I replicate the results from Table 9 in Barkowski and McLaughlin (2022, 682) and report additional results that include the necessary two-way interactions. Due to the size of the table, I separated the table by the model used. In my Table 2, I report results for the 19- to 25-year-old sample, and in my Table 3, I report the results for the 23- to 25-year-old and 27- to 30-year-old sample. I report results for the likelihood of being married and the marriage entry outcomes. Results for the likelihood of being divorced and marriage exit, which includes those widowed, are reported in Appendix B.

In Table 2, columns 1, 2, 4, and 5 correspond to results in Barkowski and McLaughlin's Table 9. Columns 3 and 6 are results from models that include all two-way interactions. The results from the replication are close to the originals, with most estimates agreeing to the thousandth digit. The replicated results find that the ACA significantly increased the likelihood of state-eligible young adults being married by around 2 to 2.6 percentage points relative to state-ineligible young adults. In column 3, when the full set of interactions is included, the estimated effect is insignificant and nearly zero. Turning to the estimated effect of state mandate eligibility, there is a significant decrease in the likelihood of being married when only state-by-year interactions are included. Once the additional interactions are included, the estimated effect decreases in magnitude, loses significance, and changes sign. The magnitude and sign of the ACA's effects on the likelihood of marriage entry among those eligible for state mandates are consistently around 0.4–0.5 percentage points regardless of the interactions included. However, when the full set of interactions is included, the effect becomes statistically insignificant. The estimated effect of state mandate eligibility on marriage entry is negatively signed across each specification and insignificant when the full set of interactions is included.

TABLE 2. Estimates of state and federal mandate interaction effects on the likelihood of being married and marriage entry, ages 19 to 25

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent variable: married			Dependent variable: marriage entry		
Under age 26						
Eligible under state mandates × ACA	0.0197*** (0.0052)	0.0261*** (0.0041)	0.0001 (0.0047)	0.0049* (0.0027)	0.0049* (0.0029)	0.0042 (0.0029)
Eligible under state mandates	−0.0362*** (0.0085)	−0.0139 (0.0084)	0.0041 (0.0059)	−0.0034 (0.0114)	−0.0074** (0.0031)	−0.0052 (0.0040)
Corresponding result in Barkowski and McLaughlin (2022)	Table 9, Column 1	Table 9, Column 2	n/a	Table 9, Column 3	Table 9, Column 4	n/a
State-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Age-state FE	No	Yes	Yes	No	Yes	Yes
Age-year FE	No	No	Yes	No	No	Yes
Observations	2,109,102	2,109,102	2,109,102	1,762,451	1762451	1762451

Notes: Estimated coefficients and standard errors (in parenthesis) are reported. Columns 1, 2, 4, and 5 are replications of the results in Barkowski and McLaughlin (2022). Columns 3 and 6 are specifications including the full set of two-way interactions. All regressions were performed using ACS person weights with standard errors clustered by state. *, **, and *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively.

TABLE 3. Estimates of state and federal mandate interaction effects on the likelihood of being married and marriage entry, ages 23–25 and 27–30

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent variable: married			Dependent variable: marriage entry		
Under age 26						
Eligible under state mandates × ACA	0.0024 (0.0041)	0.0083** (0.0036)	0.0041 (0.0040)	0.0044* (0.0025)	0.0056** (0.0022)	0.0075*** (0.0024)
Eligible under state mandates	−0.0172*** (0.0053)	0.0005 (0.0040)	0.0023 (0.0044)	−0.0048* (0.0026)	−0.0071** (0.0033)	−0.0071** (0.0035)
ACA difference-in-differences						
Effect on the state ineligible	0.0033 (0.0029)	−0.0018 (0.0028)		−0.0083*** (0.0019)	−0.0090*** (0.0017)	
Effect on the state eligible	0.0056 (0.0055)	0.0039 (0.0038)	0.0046 (0.0046)	−0.0027 (0.0026)	−0.0029 (0.0030)	0.0053 (0.0036)
Corresponding result in Barkowski and McLaughlin (2022)	n/a	n/a	n/a	Table 9, Column 5	Table 9, Column 6	n/a
State-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Age-state FE	No	Yes	Yes	No	Yes	Yes
Age-year FE	No	No	Yes	No	No	Yes
Observations	2,012,210	2,012,210	2,012,210	1,264,432	1264432	1264432

Notes: Estimated coefficients and standard errors (in parenthesis) are reported. Columns 4 and 5 are replications of the results in Barkowski and McLaughlin (2022). Columns 3 and 6 are specifications including the full set of two-way interactions. All regressions were performed using ACS person weights with standard errors clustered by state. *, **, and *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively.

In Table 3, columns 4 and 5 correspond to results in Barkowski and McLaughlin's Table 9 (2022, 682). Columns 1–3 report results for the likelihood of being married in the 23- to 25-year-old and 27- to 30-year-old sample, which are not reported in the authors' work. Columns 3 and 6 include the full set of two-way interactions. Once again, the results from the replication exercise are consistent with the original results. In this set of results, it is worth mentioning that the labeling of Barkowski and McLaughlin's Table 9 is inaccurate. The "Under Age 26" effects shown in that table are not identified from those under 26 alone. The indicator variable for eligibility includes young adults that are in the 27- to 30-year-old group. When the full set of interaction terms is included, I find small and insignificant effects for state mandate eligibility and the interaction of state mandate eligibility and the ACA. The interaction of the ACA and state mandate eligibility significantly increases the likelihood of marriage entry, with the estimate retaining significance and increasing in magnitude from 0.4 to 0.9 percentage points as interaction terms are added. State-mandated eligibility significantly reduces the likelihood of marriage entry by around 0.5 to 0.7 percentage points. In most specifications, the impact of state eligibility and the ACA on those that were state eligible appears to be offsetting. The interpretation that the results are offsetting should be viewed with caution: the variation in state mandate eligibility is limited with only 2 years preceding the ACA and most of the variation comes from eligibility expansions covering those that are too old to be eligible under the ACA mandate. The sample for the marriage entry only includes those that are unmarried (excluding those due to divorce or spousal death in the last year) and those that married in the last year. This will result in some potential issues if either policy impacts marriage; the unmarried sample will shrink in the years after the mandate goes into effect. The marriage entry results should be viewed cautiously in light of the sample selection and the lack of effect found on overall marriage (Table 2, Column 3).

Insurance and the causal pathway

The primary motivation provided by Barkowski and McLaughlin (2022) to examine the impact of dependent mandates on marriage stems from changes in the incentives to marry (or remain unmarried) for coverage. Despite the importance of insurance coverage in this motivation, Barkowski and McLaughlin provide only one set of results relating to insurance outcomes; the set of results provided uses a different sample and model than those used to examine marriage outcomes and looks at any coverage rather than ESI coverage which is the target of the dependent mandates. To further assess the plausibility of their findings, I repeat their primary model looking at insurance outcomes and employ a difference-in-differences approach to assess marriage as a mediator on the causal path from the federal dependent mandate to insurance coverage.

In Table 4, I use Barkowski and McLaughlin's main model to assess the likelihood of having ESI coverage. The table setup follows Table 1 and focuses on those aged 19 to 25 years old. Panel A reports the outcomes for the ACS sample, which only provides information on ESI coverage from 2008 onward. Panels B, C, and D use data from IPUMS CPS to evaluate insurance outcomes for the relevant period of study, 2000–2015.[2] Along with being able to better match the insurance outcome to the study period, the CPS data allows direct exploration of the type of ESI coverage. In Panels C and D, I look at the likelihood of having ESI coverage as a policyholder and having ESI coverage through a spouse's plan, respectively.

In Panel A, I find no significant changes in the likelihood of the 19- to 25-year-old ACS sample having ESI coverage. In Panel B, where the sample changes

2. The reference period for the CPS ASEC differs from the ACS. The CPS ASEC asks about coverage in the last year while the ACS asks about current coverage.

to 19- to 25-year-olds surveyed in the CPS from 2000 to 2015, I again find no significant changes in the likelihood of having ESI coverage. It is possible that the ESI coverage could be a shift in the source, so I explore potential changes in the plan policyholder in Panels C and D. In Panel C, I find no significant changes in the likelihood of being a policyholder for an ESI plan, and, in Panel D, I find no significant changes in the likelihood of being a dependent on a spouse's ESI plan.

TABLE 4. Estimates of state and federal mandate interaction effects on employer sponsored insurance coverage

	(1)	(2)	(3)	(4)	(5)
Panel A. ACS 2008–2015, Dependent variable: ESI					
Eligible under state mandates × ACA	−0.0005 (0.0044)	0.0008 (0.0037)	−0.0014 (0.0035)	−0.0008 (0.0038)	−0.0032 (0.0056)
Eligible under state mandates	0.0014 (0.0034)	−0.0009 (0.0041)	0.0011 (0.0059)	0.0048 (0.0069)	0.0066 (0.0047)
Observations	2,109,102	2,109,102	2,109,102	2,109,102	2,109,102
Panel B. CPS 2000–2015, Dependent variable: ESI					
Eligible under state mandates × ACA	0.0108 (0.0121)	0.0101 (0.0143)	0.0254 (0.0157)	0.0252 (0.0152)	−0.0038 (0.0173)
Eligible under state mandates	−0.0103 (0.0066)	−0.0034 (0.0060)	−0.0082 (0.0099)	−0.0032 (0.0101)	0.0006 (0.0103)
Observations	211,835	211,835	211,835	211,835	211,835
Panel C. CPS 2000–2014, Dependent variable: ESI policyholder					
Eligible under state mandates × ACA	0.0094 (0.0088)	0.0129 (0.0113)	0.0232 (0.0148)	0.0197 (0.0129)	−0.0046 (0.0134)
Eligible under state mandates	−0.0073 (0.0070)	0.0017 (0.0098)	0.0030 (0.0142)	−0.0171 (0.0117)	−0.0109 (0.0120)
Observations	211,835	211,835	211,835	211,835	211,835
Panel D. CPS 2000–2014, Dependent variable: ESI spouse policyholder					
Eligible under state mandates × ACA	0.0018 (0.0036)	0.0038 (0.0038)	0.0076 (0.0062)	0.0090 (0.0063)	0.0037 (0.0082)
Eligible under state mandates	−0.0007 (0.0030)	0.0017 (0.0039)	0.0056 (0.0063)	0.0022 (0.0034)	0.0040 (0.0034)
Observations	211,835	211,835	211,835	211,835	211,835
Linear state trend	Yes	Yes	No	No	No
Quadratic state trend	No	Yes	No	No	No
State-year FE	No	No	Yes	Yes	Yes
Age-state FE	No	No	No	Yes	Yes
Age-year FE	No	No	No	No	Yes

Notes: The analytic sample consists of 19–25-year-olds. Panel A uses data from the ACS and Panels B–D use data from the CPS for the indicated years. Estimated coefficients and standard errors (in parenthesis) are reported. All regressions were performed using survey provided weights (ACS or SHADAC CPS health insurance weights) with standard errors clustered by state. *, **, and *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively.

The lack of significant changes in ESI coverage in Barkowski and McLaughlin's main model is concerning. The literature on the ACA and state dependent mandates consistently finds increases in ESI coverage for young adults. The inability to find any significant changes from leveraging state eligibility and the timing of the ACA dependent mandate suggests that the variation employed is not sufficient. Finding no change in spousal coverage or coverage as a policyholder further suggests that marrying (or staying unmarried) cannot be identified as a relevant factor in this model.

Next, I estimate the effect of the federal mandate on the likelihood of having ESI and assess whether the estimated effects are sensitive to the inclusion of a marriage indicator. In the motivating story, marriage lies on the causal path to insurance coverage. When marriage is included in the regression as a control, I can explore whether the coefficient on the federal mandate significantly changes. The difference-in-difference model I employ includes the same controls as previously used in the ACS sample, along with state, year, and age fixed effects. Using the 2008–2015 ACS, I compare treated young adults (23- to 25-year-olds) to untreated young adults (27- to 30-year-olds) before and after the federal dependent mandate went into effect.

In Table 5, I report the estimated effects of the difference-in-difference analysis. Columns 1 and 3 omit any controls for marriage, and columns 2 and 4 include an indicator for marriage. Columns 1 and 2 do not control for state mandate eligibility, while columns 3 and 4 do. Across each model, the estimated effect is roughly 9.3 percentage points. The estimated effect does not differ when controls for marriage are included, which does not support marriage as a mediator.

TABLE 5. Estimates of the federal mandate on insurance coverage

	(1)	(2)	(3)	(4)
Young × Post	0.0932*** (0.0051)	0.0929*** (0.0050)	0.0929*** (0.0050)	0.0926*** (0.0049)
Married		0.1028*** (0.0085)		0.1028*** (0.0085)
Observations	2,012,210	2,012,210	2,012,210	2,012,210
Control for state mandate eligibility	No	No	Yes	Yes

Notes: The data used is the 2008–2015 ACS. The sample is limited to young adults 23–25 and 27–30 years of age. Estimated coefficients and standard errors (in parentheses) are reported. Estimates are weighted using the ACS person weights with standard errors clustered by state. *, **, and *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively.

Conclusion

Barkowski and McLaughlin (2022) contribute to the economics literature by providing the most accurate documentation of state dependent laws. They use the new set of laws to build on an interesting question first posed by Joelle Abramowitz (2016). Based on their findings, Barkowski and McLaughlin (2022) conclude that state mandates, which often contained marriage restrictions, reduced the likelihood of marriage among age-eligible individuals and that the ACA, which included no marriage restrictions, undid the previous restrictions which discouraged marriage among the state-eligible and, among the state-ineligible, it discouraged marriage to gain coverage through a spouse with employer-sponsored insurance. A careful contemplation of Barkowski and McLaughlin (2022), however, leads one to see that the identification strategy lacks the necessary secondary interaction terms for meaningful interpretation. When the proper interaction terms are included, the main results on the likelihood of being married become small and insignificant. Furthermore, the main model employed is unable to identify any impact on insurance coverage, and there is a lack of evidence that marriage acts as a mediator for the federal dependent mandate's effect on employer sponsored insurance coverage. In their supplementary analyses that explore the likelihood of being married for a narrower time frame and examine marriage flows, I find a loss of significance for results using the sample of 19 to 25 year olds. I conclude that Barkowski and McLaughlin's (2022) findings provide little evidence of dependent mandates affecting the likelihood of marriage.

Data and code

The replication materials provided by Barkowski and McLaughlin are obtainable from ICPSR (**link**). Other data and code used in this research are available from the journal website (**link**).

Appendix A. Placebo policies

To assess how the omission of age-by-year fixed effects affects inference, I rely on the randomization inference framework from Ronald Fisher (1935). This approach relies on the null hypothesis that $\tilde{\beta}_1 = 0$ to generate p-values. (The procedure outlined in this section is also applied to $\tilde{\beta}_2$.) Under the sharp null, randomly choosing units to be treated would result in an insignificant estimate for the placebo estimates. These placebo estimates can be used to construct the null distribution, where $\tilde{\beta}_1$'s p-value is calculated as

$$\frac{\sum_{i=1}^{N} 1\left(\left|\tilde{\beta}_{1,r=i}\right| \geq \left|\tilde{\beta}_1\right|\right)}{N} \times 100$$

$\tilde{\beta}_{1,r=i}$ is the estimated coefficient from the i^{th} randomly generated mandates, $\tilde{\beta}_1$ is the estimated coefficient using the actual mandates, and N is the number of randomizations. If N is less than the set of all possible randomizations, an approximate rather than exact p-value is calculated.

One advantage of this approach is that standard errors are not relied on for inference. Instead, the significance of $\tilde{\beta}_1$ is determined by whether $\tilde{\beta}_1$ falls in the tails of the null distribution. Since $\tilde{\beta}_1 = \hat{\beta}_1 + \Sigma bias$, the null distribution allows me to determine how likely a value as extreme as $\tilde{\beta}_1$ can be found due to chance. This approach is more useful than using the t-statistic $\frac{\tilde{\beta}_1}{se\left(\tilde{\beta}_1\right)}$, which can be rewritten as $\frac{\hat{\beta}_1 + \Sigma bias}{se\left(\tilde{\beta}_1\right)}$, because the bias is included in the construction of the null distribution. The t-statistic from the misspecified model can result in reporting significant effects solely due to bias.[3]

To implement randomization inference, I randomize at the state level rather than the individual level. This is similar to the cluster-level randomization inference outlined in Thomas Barrios et al. (2012). I construct a null distribution by using 1,999 sets of placebo state policies. For each iteration, I randomly draw 33 states to implement a dependent mandate, then randomly assign age eligibility. I mirror the actual policies from Barkowski and McLaughlin (2022) by randomly assigning some policies outside the sample period, changes in eligibility requirements, and some policies coinciding with the ACA.

Before discussing the randomization process, it is worthwhile to discuss the temporal distribution of policies and their amendments relative to the sample period. The 33 treated states can be categorized into six groups:

I. Six states adopted a policy prior to the sample period.
II. One state adopted a policy prior to the sample period and reduced the

3. One example of using randomization inference to overcome issues with t-statistics—due to one treated cluster—can be seen in Kaestner (2016).

eligibility during the sample period.

III. Three states adopted a policy prior to the sample period and expanded eligibility during the sample period.
IV. Fifteen states adopted a policy in the sample period.
V. Three states adopted a policy in the sample period and expanded eligibility during the sample period.
VI. In five[4] states, policy adoption overlapped with the ACA adoption in 2010.

In generating the placebo policies, I keep these same features intact. I randomize[5] by creating a sorting variable drawn from the uniform distribution and then order the states from smallest to largest values of the sorting variable. Next, I use this ordering to create placebo treatments for the 33 states with the smallest values of the sorting variable. I outline the process for each of the six groups below.

I. For each of the first six states, I code the year of adoption as 2000 for simplicity. Next, I generate the placebo age threshold by drawing from uniformly distributed integers on the interval [19,25].
II. For the seventh state, I code the year of initial policy adoption as 2000. I generate the initial placebo age threshold by drawing from the interval [19,25]. I draw a date when the policy is contracted from the interval [2001,2009] and a stricter age threshold on the interval [18, original placebo age].
III. For each of the eighth through tenth states, I code the year of initial policy adoption as 2000. I generate the initial placebo age threshold by drawing from the interval [19,24]. I draw a date when the policy is expanded from the interval [2001,2009] and a more lenient age threshold on the interval [original placebo age, 25].
IV. For each of the eleventh through twenty-fifth states, I draw a date when the policy goes into effect from the interval [2001,2009] and draw an age threshold from the interval [19,25].
V. For each of the twenty-sixth through twenty-eighth states, I draw a date when the policy goes into effect from the interval [2001,2008] and draw an age threshold from the interval [19,24]. To create a placebo policy expansion, I draw a date from the interval [original placebo year, 2009] and an age threshold from [original placebo age, 25].

4. In four of the states, the state dependent mandates take effect in 2010, but Pennsylvania is coded as taking place in 2010 in the replication files despite being listed as going into effect in 2009. I follow the coding in the replication files to be consistent with Barkowski and McLaughlin (2022).
5. Randomization is done using STATA's runiform and runiformint functions.

VI. For each of the twenty-ninth through thirty-third states, I code the initial year of treatment as 2010. I then generate the placebo age threshold by drawing from the interval [19,25].

With the policies generated, I create a measure of placebo eligibility and re-estimate each of the Equation 5 variants reported in Table 4 columns 1 through 4 in Barkowski and McLaughlin (2022, 672). I save the coefficients on $ELIG_{ast} \times ACA_t$ and the coefficient on $ELIG_{ast}$ for each of the four models. I repeat this for a total of 1,999 placebo regressions. I use the distribution of the 2,000 total regressions (including the true policy) to see how many values exceed the coefficients under the true policy. The corresponding histograms in Figure A1 show that all, or nearly all, of the placebo coefficients are larger than the coefficient from the actual policies in columns 1–3. The specification in column 4 fares better, but it still suffers from the average coefficient being approximately 0.044. Due to the model misspecification, across all 8,000 regressions corresponding to columns 1–4, only five would fail to reject the null hypothesis in a t-test.

TABLE A1. P-values from replication and placebos

	(1)	(2)	(3)	(4)	(5)
Eligible under state mandates × ACA					
P-value	0.047	0.011	0.000	0.000	0.490
Placebo p-value	0.9995	0.999	0.996	0.110	0.291
Eligible under state mandates					
P-value	0.042	0.018	0.008	0.362	0.940
Placebo p-value	0.307	0.2675	0.181	0.55	0.922
Corresponding result in Barkowski and McLaughlin (2022)	Table 4, Column 1	Table 4, Column 2	Table 4, Column 3	Table 4, Column 4	n/a
Linear state trend	Yes	Yes	No	No	No
Quadratic state trend	No	Yes	No	No	No
State-year FE	No	No	Yes	Yes	Yes
Age-state FE	No	No	No	Yes	Yes
Age-year FE	No	No	No	No	Yes
Observations = 3,199,012					

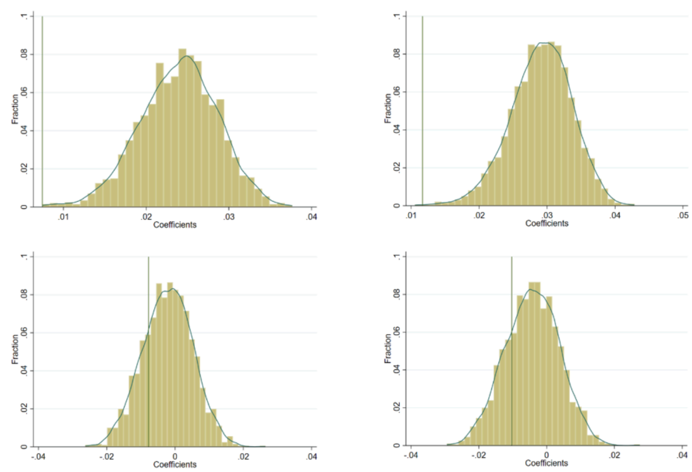
Notes: P-values from the replication are reported along with p-values based on the placebo policies. Columns 1–4 correspond to results in Barkowski and McLaughlin (2022, 672). Column 5 corresponds to the specification including the full set of two-way interactions. All regressions were performed using ACS person weights with standard errors clustered by state.

Figure A1. Placebo coefficient distribution

(1) (2)

Placebo coefficient distribution for $\tilde{\beta}_1$

Placebo coefficient distribution for $\tilde{\beta}_2$

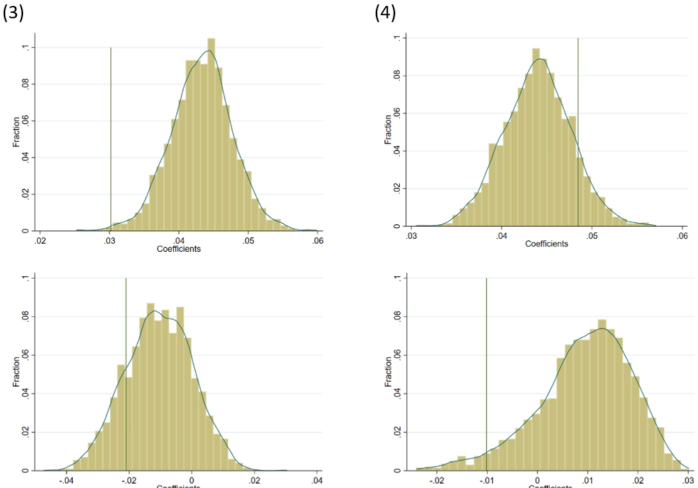


	(1)	(2)
Linear state trend	Yes	Yes
Quadratic state trend	No	Yes
State-year FE	No	No
Age-state FE	No	No
Age-year FE	No	No

(3) (4)

Placebo coefficient distribution for $\tilde{\beta}_1$

Placebo coefficient distribution for $\tilde{\beta}_2$

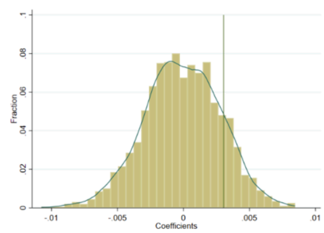


	(3)	(4)
Linear state trend	No	No
Quadratic state trend	No	No
State-year FE	Yes	Yes
Age-state FE	No	Yes
Age-year FE	No	No

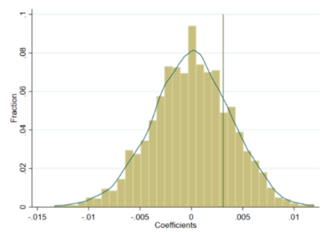
Figure A1 continued. Placebo coefficient distribution

(5)

Placebo coefficient distribution for $\tilde{\beta}_1$



Placebo coefficient distribution for $\tilde{\beta}_2$



	(5)
Linear state trend	No
Quadratic state trend	No
State-year FE	Yes
Age-state FE	Yes
Age-year FE	Yes

Notes: Columns 1–4 correspond to the same numbered columns in Table A1. Each plot shows the histogram and Epanechnikov kernel density estimate for the 2,000 coefficients (1,999 from placebos and one from the actual policy). The vertical line in each plot represents the coefficient from the actual policies.

The results for $\tilde{\beta}_2$, the coefficient on $ELIG_{ast}$, are similar. In columns 1–3, the RI p-values range from 0.181 to 0.307. In column 4, the RI p-value is 0.550. Figure A1 shows that the placebo coefficients have means closer to zero for columns 1 and 2. The means for columns 3 and 4 are roughly −0.011 and 0.09, respectively. Again, the misspecification leads to the over-rejection of the null hypothesis in a t-test; of the 8,000 regressions, 2,216 would result in a rejection of the null hypothesis.

Appendix B. Divorce and marriage exit

TABLE B1. Estimates of state and federal mandate interaction effects on the likelihood of being divorced and marriage exit, ages 19 to 25

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent variable: divorced			Dependent variable: marriage exit		
Under age 26						
Eligible under state mandates × ACA	0.0008 (0.0012)	0.0017 (0.0010)	0.0000 (0.0011)	−0.0004 (0.0033)	−0.0003 (0.0035)	−0.003 (0.0038)
Eligible under state mandates	−0.0069*** (0.0017)	−0.0031** (0.0015)	−0.0018 (0.0016)	0.0019 (0.0024)	0.0035 (0.0047)	0.0023 (0.0042)
Corresponding result in Barkowski and McLaughlin (2022)	n/a	n/a	n/a	Table 9, Column 3	Table 9, Column 4	n/a
State-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Age-state FE	No	Yes	Yes	No	Yes	Yes
Age-year FE	No	No	Yes	No	No	Yes
Observations	2,109,102	2,109,102	2,109,102	376,553	376,553	376,553

Notes: Estimated coefficients and standard errors (in parenthesis) are reported. Columns 4 and 5 are replications of the results in Barkowski and McLaughlin (2022). Columns 3 and 6 are specifications including the full set of two-way interactions. All regressions were performed using ACS person weights with standard errors clustered by state. *, **, and *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively.

TABLE B2. Estimates of state and federal mandate interaction effects on the likelihood of being divorced and marriage exit, ages 23–25 and 27–30

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent variable: divorced			Dependent variable: marriage exit		
Under age 26						
Eligible under state mandates × ACA	0.0001 (0.0018)	−0.0005 (0.0013)	−0.0010 (0.0014)	−0.0008 (0.0025)	0.0005 (0.0024)	0.0004 (0.0022)
Eligible under state mandates	−0.0007 (0.0026)	0.0027** (0.0012)	0.0026** (0.0013)	0.0018 (0.0017)	0.0037 (0.0034)	0.0019 (0.0031)
ACA difference-in-differences						
Effect on the state ineligible	0.0041 (0.0012)	0.0042*** (0.0012)		0.0012 (0.0013)	-0.0001 (0.0012)	
Effect on the state eligible	0.0058*** (0.0016)	0.0055*** (0.0015)	0.0006 (0.0020)	−0.0034 (0.0022)	−0.0035 (0.0023)	−0.0017 (0.0029)
Corresponding result in Barkowski and McLaughlin (2022)	n/a	n/a	n/a	Table 9, Column 5	Table 9, Column 6	n/a
State-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Age-state FE	No	Yes	Yes	No	Yes	Yes
Age-year FE	No	No	Yes	No	No	Yes
Observations	2,248,060	2,248,060	2,248,060	851,830	851,830	851,830

Notes: Estimated coefficients and standard errors (in parenthesis) are reported. Columns 4 and 5 are replications of the results in Barkowski and McLaughlin (2022). Columns 3 and 6 are specifications including the full set of two-way interactions. All regressions were performed using ACS person weights with standard errors clustered by state. *, **, and *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively.

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About the Author

Aaron M. Gamino is an assistant professor in the Economics and Finance Department of the Jennings A. Jones College of Business at Middle Tennessee State University. He received his Ph.D. and M.A. in Economics from Vanderbilt University. He received his B.A. in economics and philosophy from the University of Illinois at Urbana-Champaign. His interests include demography, health, history, and labor. His email address is aaron.gamino@mtsu.edu.

Scott Barkowski and Joanne Song McLaughlin's reply to this article