



The Rise of the Nones across the United States, 1973 to 2018: State-Level Trends of Religious Affiliation and Participation in the General Social Survey

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Abstract: Although there has been a fast rise in the share of Americans reporting no religion, it is unclear whether this trend has affected different parts of the country equally. Against this backdrop, we apply dynamic multilevel regression and poststratification (Dynamic MRP) to General Social Survey data over the period 1973 to 2018 to estimate state-level religious trends. We validate our estimates against external benchmarks, finding that they perform well in terms of predictive accuracy. Substantively, we find steeper increases in the share of religious nones in states that had more nones to begin with. Moreover, whereas state-level increases in the share of religious nones are strongly linked to declines in occasional church attendance and moderate religious identification, the associations with trends in regular attendance and strong identification are much weaker. States have thus not only diverged in their share of religious nones but also experienced different degrees of religious polarization.

Keywords: religion; secularization; polarization; geography; MRP; General Social Survey

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THE fast rise in the share of Americans reporting no religion is one of the major changes in American society captured in social surveys over the past decades (Hout and Fischer 2002). Together with declines observed in other measures of religiosity, this has led some prominent scholars to conclude that America is no longer an exception to the secularizing trend taking place in most of the Western world (Voas and Chaves 2016). Although this interpretation remains contested, the "rise of the nones" undeniably represents a notable "stylized fact" (Hirschman 2016) in the sociology of religion. Rooted in generational succession, political backlash, and cultural conflict (e.g., Hout and Fischer 2014; Putnam and Campbell 2010), the rise of the nones furthermore gives rise to religious polarization, as moderate adherents are leaving church at higher rates than strong affiliates (Schnabel and Bock 2017; Voas and Chaves 2018).

Religion in America is, however, unevenly distributed across the country. Since Zelinsky's classic work (1961), cultural geographers have shown that different American regions have distinct religious cultures, each with its own mix of religious traditions (Bauer 2012; Crawford 2005; Jordan 2007). Likewise, sociologists of religion have documented that religious affiliation rates and levels of religious involvement vary substantially across the country, being high in, for example, the Bible Belt and low in the Pacific Northwest (e.g., Silk 2005; Smith, Sikkink, and Bailey 1998). In this study, we ask whether different areas may also have experienced different patterns of religious change over the past decades. In particular,

we examine whether the rise of the nones has been equally powerful across the country or whether some areas have been more affected by this trend than others. Considering the central role of religion in American social and civic life, differential local trends in religion can have far-reaching implications for social processes at the individual as well as community level.

Motivated by similar objectives, several recent studies have compared trends in the share of religious non-affiliates between regions. These studies show that all four U.S. Census regions have experienced an upward trend in the share of people reporting no religion over the period 1985 to 2010 (Wilkins-Laflamme 2014), although the trend seems to have somewhat different implications for religious polarization across the nine U.S. Census divisions. Dilmaghani (2020), for example, finds that New England witnessed a decrease in polarization between 2008 and 2016, whereas West South Central states (i.e., Arkansas, Louisiana, Oklahoma, and Texas) experienced the opposite trend. However, as these studies focus on large regions over a relatively short period, the trends they report may obscure important variation within each region. The question of how long-term trends in religious affiliations and other measures of religiosity vary across states or smaller geographies thus remains unanswered.

A key reason for this evidence gap concerns the absence of data that readily track changes in religiosity across local areas over a long period of time. There are several large-scale data sources that could be used for studying the evolution of religious populations down to the local level, yet, as we will argue, these sources all suffer from serious shortcomings. We therefore adopt a different approach, relying on multilevel regression and poststratification (MRP). First proposed by Gelman and Little (1997), MRP has been widely applied to estimate area-level public opinion from national surveys of modest sample sizes (e.g., Butz and Kehrberg 2016; Gelman et al. 2008; Hanretty, Lauderdale, and Vivyan 2018; Kestellec et al. 2015). Most of these studies have a static focus, deriving estimates for a single point or period in time. Recently, however, Gelman and colleagues (2018) have proposed an extension of MRP to generate subnational time-series estimates, labeling this extension “Dynamic MRP” or “MRP over time.”

We apply this Dynamic MRP technique to estimate state-level religious trends between 1973 and 2018 using the General Social Survey (GSS). We consider various measures of religiosity, namely, whether people belong to a religion, how often they attend religious services, and how strongly they identify with their religion. Although we focus on states as areal units, the Dynamic MRP approach can in principle also be applied to other subnational units, including lower-level areas (e.g., counties) and non-areal units (e.g., specific demographic groups).

By providing estimates of state-level trends in key measures of religiosity, we offer new insights on how the rise of the nones has taken shape over the past decades. We show that although all states have experienced a significant rise in their share of religious nones, increases have been larger in states that already started off with more nones in the 1970s. Thus, contrary to the longstanding prediction that cultural differences between states would fade under the influence of internal migration, mass media, and other factors (e.g., McKinney and Bourque 1971), religious gaps between states have actually grown, at least for the time being. Untangling these

trends further, we find that state-level increases in the share of religious nones are strongly linked to declines in *occasional* church attendance and *moderate* religious identification, whereas the associations with trends in *regular* church attendance and *strong* religious identification are substantially weaker or nonexistent. In line with earlier claims based on nationwide analyses (e.g., Hout and Fischer 2014; Voas and Chaves 2016), this finding indicates that religious nones have primarily gained ground at the expense of weak religious adherents. As a result, religious polarization in terms of a “hollowing of the middle” has been strongest in states that have witnessed bigger increases in their share of nones.

In addition to refining our understanding of how the American religious landscape has changed, the estimates obtained in this study represent a valuable resource for future research in many fields of sociology, uncovering trends regarding a vital dimension of state-level culture. Among other things, these data—spanning nearly half a century—may help researchers to assess the potential consequences of religious change for civic life, political behavior, and public opinion, among many other domains. To facilitate such research, we make our estimates publicly available, together with the underlying code, so others can improve upon our estimates.¹

More generally, our analysis demonstrates the utility of Dynamic MRP for estimating area-level trends in social attitudes, preferences, and behaviors. Although sociologists have been relatively slow to adopt MRP, let alone its dynamic sibling (see Claassen and Traunmüller [2020] for an exception), we show that Dynamic MRP can be fruitfully employed to generate subnational, long-term time series from national surveys. Systematic comparisons with external benchmarks available for several years show that our Dynamic MRP estimates perform well in terms of predictive accuracy—indeed just as well as the external benchmarks score in comparison with one another. Hence, our study stresses the “democratizing” potential of Dynamic MRP: one does not necessarily need to field a series of expensive, large-scale surveys to track key social outcomes at a subnational level. Rather, an easily accessible data source such as the GSS can already offer substantial leverage. Dynamic MRP thus further enhances the already impressive value of the GSS (Marsden, Smith, and Hout 2020) and other existing data sources.

In the remainder of this article, we first discuss the challenges in obtaining reliable area-level estimates of religiosity using conventional approaches. We then introduce our Dynamic MRP approach and the data that we use to estimate state-level trends in religiosity. Next, we assess the validity of the resulting estimates, followed by a discussion of how the rise of the nones has unfolded across states. We conclude by considering the strengths and limitations of our approach as well as the implications of our findings for debates on America’s changing religious landscape.

Challenges in Measuring Local Religious Trends

Tracking religious composition and participation at the local level has been a long-standing challenge for scholars of American religion, as the U.S. Census has not collected information on religion since the 1950s, whereas most social surveys do not have sample sizes large enough to obtain reliable estimates at the local level.

Researchers have, therefore, typically relied on one of two approaches for obtaining area-level religiosity estimates.

The first approach uses occasional surveys with unusually large samples, such as the American Religious Identification Survey (ARIS), the Pew Religious Landscape Study (PRLS), and the American Values Atlas (AVA). By virtue of their sample sizes and sampling strategies, these sources can provide estimates of religious composition for states or even smaller geographic units (Lim 2013). However, they are of limited value for tracking the religiosity of areas over time because they are only available for certain years, leaving major gaps, especially before the turn of the century.² Moreover, these surveys suffer from low response rates (typically 10 to 25 percent) and are not directly comparable with one another because of differences in sampling designs, interview modes, and the wording and coding of key questions. Furthermore, only the PRLS collects information beyond religious affiliations (e.g., frequency of religious service attendance, strength of religious identification), whereas the utility of the AVA is further constrained by the fact that the underlying individual-level data are not publicly available.

The second approach relies on the decennial denomination surveys of the Religious Congregations and Membership Study (RCMS). Recently, two research teams independently harmonized the RCMS data from 1980 onwards to construct a longitudinal data set of the number of adherents of the major Christian denominations at the state and county level (Bacon, Finke, Jones 2018; Olson et al. 2020). These efforts have produced valuable resources, which open up new opportunities for students of American religion, as demonstrated by Olson et al. (2020). Yet, also the RCMS has critical limitations for tracking area-level religious trends. To begin with, affiliations are reported centrally by each denomination rather than by individual adherents, with denominations likely varying in the accuracy of their membership records as well as how they define membership in the first place. More importantly, the RCMS does not measure religious non-affiliation or levels of religious involvement. Although one could technically still obtain rates of non-affiliation by subtracting the total number of religious adherents in an area from the local population size, Lim (2013) shows that this approach does not yield estimates that are comparable to estimates from large-scale surveys. Finally, the denominations covered by the RCMS vary over time, with the earlier data failing to identify various important denominations, including black Protestants and several non-Christian traditions.

In short, notwithstanding the value of the RCMS, ARIS, PRLS, and AVA, these sources have severe limitations for tracking long-term subnational trends in religiosity. In this study, we turn to another data set—the GSS—which, with the help of Dynamic MRP, enables us to consistently track area-level religious changes between 1973 and 2018. Our application focuses on all 50 American states and the District of Columbia, given the presumed significance of states for capturing variation in cultural, historical, and institutional contexts (e.g., Elazar 1966).

Tracking State-Level Religious Trends Using the GSS

The GSS is a landmark resource for studying religious change in America. Since its inception in 1972, each wave of the GSS has included questions on religious

affiliations and practices, with data collected at least every other year. Crucially, the format and content of these questions have remained the same over time. The GSS also benefits from far higher response rates than the ARIS, PRLS, and AVA with an average response rate of around 75 percent, and compared with the RCMS, it offers measures of non-affiliation and intensities of involvement. As a result, the GSS is well suited for tracking religious change in America. In fact, most stylized facts about recent changes in American religion, including the rise of the nones, are largely based on the GSS (Marsden et al. 2020).

Despite these strengths, the GSS suffers from relatively small sample sizes. With about 1,400 to 3,000 respondents, each survey wave contains only a small number of respondents for most states and the smallest 10-odd states are not identified at all in most waves.³ In addition, the GSS is not designed to be representative at the state level. So even for states that are identified in all years, we would end up with imprecise and possibly biased trend estimates if we were to naïvely look at the proportion of survey respondents with certain religious characteristics in a given year. A partial solution to this problem is to pool information from multiple GSS waves; however, such pooling might obscure underlying trends, and by ignoring all data outside the pooling window, this approach fails to make efficient use of all available information. Furthermore, the pooling solution has a strong arbitrary element, as the researcher must decide on an appropriate pooling window, and it also leaves the problem of non-representative state-level samples unaddressed.

To avoid these problems and to unlock the full potential of the GSS for tracking state-level religious trends, we apply a dynamic variant of MRP. Since Gelman and Little (1997) first proposed the MRP method, it has been elaborated upon and extended by, among others, Park, Gelman, and Bafumi (2004), Lax and Phillips (2009), Kastellec et al. (2015), and Leemann and Wasserfallen (2017). In a nutshell, MRP models individual responses to national surveys in order to generate predicted outcomes for various sociodemographic subgroups and then weights these predictions based on the size of the subgroups in the relevant population (e.g., a particular state) so as to obtain estimates of the prevalence of the outcome of interest within that population.

To date, MRP has been primarily applied by political scientists to estimate subnational public opinion on issues such as same-sex marriage (Lax and Phillips 2009), immigration (Butz and Kehrberg 2016), U.S. Supreme Court candidates (Kastellec et al. 2015), and the European Union (Hanretty et al. 2018). In comparison, its adoption in sociology has been slower, although the tide appears to be turning, with recent studies using MRP to estimate state-level income mobility (Bloome 2015), state-level attitudes to LGBT employment rights (Dixon, Kane, and DiGrazia 2017), and state-level support for criminal sentencing policies (Duxbury 2021). A few studies have also applied MRP to estimate the size of small religious groups at the national level, such as the proportion of Jews in the United States and Canada (Magidin de Kramer et al. 2018; Tighe et al. 2010) and the proportion of Muslims, Hindus, and Jews in the United Kingdom (Claassen and Traunmüller 2020). Among these studies, the one by Claassen and Traunmüller (2020) is most ambitious, investigating the prevalence of different religious traditions within subgroups (e.g., young women with a degree) over time.

We build on this work and provide a rigorous test of the value of Dynamic MRP for estimating the size of religious groups over time. Our primary departure from earlier studies is that we derive area-level estimates of religious populations, as opposed to national estimates. We also focus on a wider set of outcomes, and, like Claassen and Traunmüller (2020), we estimate trends over time. More specifically, we consider a period that spans nearly 50 years—significantly longer than in any prior application of Dynamic MRP—and covers major religious changes. As such, our study provides an especially challenging test of the utility of Dynamic MRP.

Our Application of Dynamic MRP

MRP consists of two main steps. First, multilevel regression is used to model some individual-level response to a national survey (e.g., having a religious affiliation) as a function of various sociodemographic and area-level (or other group-level) characteristics. The multilevel regression model treats individual observations as nested within areal units and partially pools information across areal units to generate its estimates. This partial pooling of information makes for a more efficient estimation process and results in more precise area-level estimates. Second, the regression results are used to calculate predicted outcomes for a wide range of respondent types, as defined by key sociodemographic characteristics and area of residence. These predictions are then aggregated at the area level while applying weights to reflect the prevalence of each respondent type within the population of each area. This poststratification reduces any bias in the area-level estimates that may result from survey-related issues such as selective nonresponse and undercoverage of certain sociodemographic groups.

Whereas the original MRP method partially pools information across areas, we follow recent work by Gelman et al. (2018) and Claassen and Traunmüller (2020) and partially pool information both across space and over time. This means, for example, that our estimate of the percentage of religious nones in Wisconsin in 2000 is informed not merely by the number of nones observed in Wisconsin in the 2000 GSS but also by the number of nones observed in, say, Minnesota or Oregon in 2000 (partial pooling across space) and the number of nones observed in Wisconsin and other states in, for example, 1975, 1990, or 2010 (partial pooling over time). The exact amount of information pooling across states and years is endogenously determined by the patterns in our data, with greater pooling toward the overall mean when the variance in outcomes across states or years is smaller and when states or years have fewer observations.

Because of the explicit modeling of dependencies over time, Gelman et al. (2018) call this approach “Dynamic MRP” or “MRP over time.” The core strength of Dynamic MRP is that, by partially pooling information over time, we can incorporate substantially more data when deriving estimates for any state–year combination, which will be especially helpful for states with only a few respondents (or none at all) in certain years. Dynamic MRP thus helps to achieve greater precision and accuracy in tracking trends. Compared with earlier MRP approaches to estimating trends, which rely on the repeated application of “Static MRP” to subsamples for

different time periods, Dynamic MRP also has the benefit of parsimony, requiring only one multilevel model per outcome for the entire time window.

We start our analysis by running multilevel regressions for whether respondents identify as religious none, using a dummy variable that equals 1 if respondents choose “no religion” as religious preference and 0 otherwise. “Don’t know” and “no answer” responses (0.5 percent of the GSS sample) have been coded as 0 to capture the prevalence of “no religion” among *all* respondents. We additionally fit multilevel models for frequency of religious service attendance and strength of religious identification. For religious service attendance we consider two dummy variables—for weekly attendance and no attendance—and for strength of religious identification we consider one dummy variable, which captures whether people strongly identify with their religion.⁴ Any missing values (0.8 and 3.0 percent of the sample for, respectively, religious attendance and religious identification) have again been coded as 0.

Although we focus on these three indicators of religiosity, we also fit multilevel models to estimate affiliation rates for the four major Christian traditions: Catholic, mainline Protestant, evangelical Protestant, and black Protestant.⁵ We use the resulting estimates for additional validity checks of our Dynamic MRP approach. We identify these traditions by recoding respondents’ affiliations in accordance with the RELTRAD scheme, as proposed by Steensland et al. (2000) and updated by Stetzer and Burge (2016), while coding generic “Protestant,” “Christian,” and “Inter/non-denominational” responses that could not be assigned to any particular tradition (3.8 percent of the sample) as 0. We model all outcomes using logistic multilevel regressions based on maximum likelihood estimation, implemented with the “glmer()” function in R. All models are fit to the cumulative GSS data set over the period 1973 to 2018, comprising 62,147 cases.^{6,7}

Equation (1) summarizes the setup of our multilevel regressions, which model the log odds of a positive outcome for individual i in state s at time t :⁸

$$\begin{aligned} \text{Logit}(y_{ist} = 1) = & \beta^0 + \beta^{sr} \cdot \text{SexRace}_{ist} + \beta^{age} \cdot \text{Age}_{ist} + \beta^{ed} \cdot \text{Educ}_{ist} \\ & + \beta^{reg} \cdot \text{Region}_s + \beta^{cd} \cdot \text{CongDens}_{st} + \beta^{rv} \cdot \text{RepVote}_{st} \\ & + (\beta^{year} + \gamma_s^{year}) \cdot \text{Year}_t \\ & + \gamma_s^0 + \gamma_t^0. \end{aligned} \quad (1)$$

On the right-hand side of Equation (1), we find the overall model intercept (β^0), followed by several terms that capture the influence of individual-level sociodemographic characteristics that may affect religious outcomes as well as survey nonresponse. More specifically, sex (male vs. female) and race (white, black, Hispanic, other) are included via their interaction, and age (18 to 29, 30 to 44, 45 to 64, 65 or older) and educational attainment (no high school degree, high school degree, some college, college degree) are included as categorical variables. We estimate fixed coefficients to capture the influence of these sociodemographic covariates.

Skipping to the last line of Equation (1), the term γ_s^0 represents a random intercept at the state level. This random intercept models any time-invariant state-level effects on individual responses that cannot be accounted for by the other model

components, and it ensures that our models partially pool information across states. Similarly, the term γ_t^0 denotes a random intercept at the year level, which accounts for any unexplained nationwide variation between survey years and ensures that our models partially pool information across years. By instructing our models to partially pool information across both states and years, these random intercepts are critical ingredients to our Dynamic MRP approach.

The second line of Equation (1) includes state-level predictors, which are added to improve the model predictions and to help determine an appropriate degree of information pooling across states. Prior research has shown that the inclusion of such area-level predictors is crucial to avoid an overly strong shrinkage of the area-level estimates toward the national average (e.g., Buttice and Highton 2013). In our case, we include three sets of state-level predictors with their influence modeled using fixed coefficients: (i) the Census region that a state belongs to (Northeast, Midwest, South, West),⁹ (ii) its number of religious congregations per 1,000 residents (from the RCMS), and (iii) its Republican vote share in presidential elections (American Presidency Project 2021). Which congregational density measures are included depends on the outcome of interest: for example, when modeling whether people identify as evangelical Protestant, we only include the density of evangelical congregations, yet when modeling whether people identify as religious none or how often they attend religious services, we include congregational density variables for all religious traditions (i.e., evangelical Protestant, mainline Protestant, black Protestant, Catholic, other). For all congregational densities, we apply linear interpolations between the years 1980, 1990, 2000, and 2010 (i.e., the years for which RCMS data are available) while assigning all years prior to 1980 (after 2010) the same values as for 1980 (2010).¹⁰ For the Republican vote share variable, we linearly interpolate values for between-election years. This variable is, however, only included in the models for religious service attendance and strength of religious identification, as it is an insignificant predictor in all religious affiliation models.¹¹

Finally, the third line of Equation (1) adds a year variable (centered around 1990 and measured in units of 10 years). This variable helps to model any time trends and informs the pooling of information across years by acknowledging that years closer in time tend to be more strongly related to one another. Importantly, the coefficients of the year variable are modeled as random slopes that may vary across states, via the parameter γ_s^{year} . We thus explicitly allow different states to experience different religious trajectories. We have also fit regressions where time trends were modeled using quadratic or piecewise linear functions (with a hinge at 1990, similar as in Hout and Fischer [2002]), again allowing for state-specific slopes. However, where such modifications resulted in improvements in model fit, the gains were minimal, whereas in other cases the added complexity resulted in convergence to boundary solutions. What is more, in terms of predictive accuracy vis-à-vis external benchmarks, Dynamic MRP estimates based on linear time trend specifications perform just as well as Dynamic MRP estimates based on nonlinear time trend specifications (see Figures S6 and S7 in the online supplement). For the sake of parsimony and consistency, we therefore prefer specifications with linear time trends.¹²

Tables S3 and S4 in the online supplement summarize the results of the multi-level regressions. The reported coefficient estimates by and large conform to our prior expectations. For example, we observe that women tend to be more religious than men, that age and religiosity are generally positively associated, that the association between education and religiosity depends on the outcome considered, and that people are more likely to be affiliated with a particular tradition if they live in a state with more congregations of that tradition. The random effect estimates of the models also provide a first indication that there is a reasonable amount of variation between states in their levels and trends for the religious outcomes under consideration.

We subsequently use these regression results to generate predicted probabilities for each outcome of interest for 128 respondent types for each state–year combination. The respondent types are based on the full cross-classification of the sociodemographic variables included in the multilevel regressions, that is, 2 sex categories \times 4 race categories \times 4 age categories \times 4 education categories. This results in a total of 128 respondent types \times 51 states \times 31 survey waves = 202,368 predictions for each outcome of interest. We next determine the prevalence of each respondent type within a given state–year combination using the U.S. Census for the period 1970 to 2000 (applying linear interpolations for intercensal years) and the American Community Survey (ACS) for the period 2001 to 2018.¹³ We then weight the model predictions for each respondent type by its prevalence in the Census or ACS data to obtain estimates of the proportion of people for each state–year combination who belong to a certain tradition, who attend religious services with a certain frequency, or who strongly identify with their religion. This weighting ensures that any biases in the composition of the state-level samples in the GSS versus the underlying state-level populations are corrected for. We finally linearly interpolate the Dynamic MRP estimates for years in which no GSS survey took place.

The Validity of the Dynamic MRP Estimates

We assess the accuracy of our Dynamic MRP estimates by comparing them with external benchmarks that are available for selected years from the ARIS, PRLS, and AVA. Although these sources are themselves of limited use for mapping state-level religious trends, they offer valuable reference points for appraising the credibility of our Dynamic MRP estimates. That said, it is relevant to bear in mind that these external sources may contain errors of their own when it comes to tracking states' "true" religious composition—more on this later.

To see whether the predictive accuracy of our Dynamic MRP estimates varies over time, we conduct benchmark comparisons for multiple years: 1990 (based on ARIS 1990), 2001 (based on ARIS 2001), 2008 (based on ARIS 2008 and PRLS 2007), and 2014 (based on PRLS 2014 and AVA 2014).¹⁴ For religious attendance and strength of religious identification, we only look at 2008 and 2014 because the PRLS is the only benchmark survey with data on these outcomes. To ensure comparability, we recoded religious affiliations in each benchmark survey in line with the RELTRAD scheme (Steensland et al. 2000; Stetzer and Burge 2016) that

we used to classify religious traditions in the GSS.¹⁵ For religious attendance and strength of religious identification, harmonization is somewhat trickier, because the GSS and PRLS have different response options for these items, which do not perfectly map onto each other. More generally, several sources of variation remain, relating to response rates, question wording, interview mode, et cetera.

To evaluate the relative merits of our Dynamic MRP approach, we also consider two sets of GSS-based estimates that were derived using alternative approaches. First, we consider the “Disaggregation” approach, which divides the GSS data set into subsamples for each state–year combination and then calculates the proportion of people within each of these subsamples who belong to a particular tradition, attend church with a particular frequency, or strongly identify with their religion. To improve the resulting estimates, we apply the “WTSSALL” survey weight and pool data across five-year intervals such that the 2010 estimates are, for example, based on all GSS data between 2008 and 2012.¹⁶ Second, we examine estimates based on “Repeated MRP,” whereby we fit similar regressions as described above, except for the exclusion of the time-related components, to subsamples for different time periods, again pooling data across five-year windows. In contrast to Dynamic MRP, which partially pools information across all survey years, this Repeated MRP procedure applies complete pooling within five-year intervals while barring any pooling of information from outside these intervals.

Figures 1 and 2 summarize the results of our comparisons between the three sets of GSS-based estimates—Dynamic MRP, Repeated MRP, Disaggregation—and the external benchmarks from the ARIS, PRLS, and AVA. We consider three metrics: (i) the pairwise correlations between the GSS-based estimates and the benchmarks, (ii) the mean absolute percentage errors (MAPEs) of the GSS-based estimates vis-à-vis the benchmarks, and (iii) the corresponding mean absolute errors (MAEs).¹⁷

Figures 1 and 2 show that the Dynamic MRP estimates perform well in terms of their predictive accuracy vis-à-vis the external benchmarks, for all outcomes and for all years. The benchmark correlations for the Dynamic MRP estimates in the top-left panels are around 0.80 or higher, up to coefficients close to 1.00 for black Protestants and Catholics. These high correlations suggest that our Dynamic MRP estimates are reliable indicators for tracking changes in religious landscapes. This conclusion is underscored by the MAPEs for the Dynamic MRP estimates (top-right panels), which are safely within the 30 percent range for most outcome–year combinations. Although we observe larger MAPEs for black Protestants in some years, this mainly reflects that black Protestants constitute small populations in most states such that small deviations in absolute terms translate into large deviations in relative terms. As an illustration, the MAPE of 46 for black Protestants in 2014 corresponds to an MAE of less than two percentage points. More generally, most MAEs for the Dynamic MRP estimates amount to less than five percentage points (bottom-left panels). The key exception concerns the proportion of people who strongly identify with their religion, with MAEs of around 15 to 20 percentage points. Further analyses reveal that this is because the Dynamic MRP estimates for this outcome are systematically lower than the corresponding PRLS estimates, plausibly reflecting differences in question wording and response options between the GSS and PRLS. Apart from this, both sets of estimates are largely consistent.

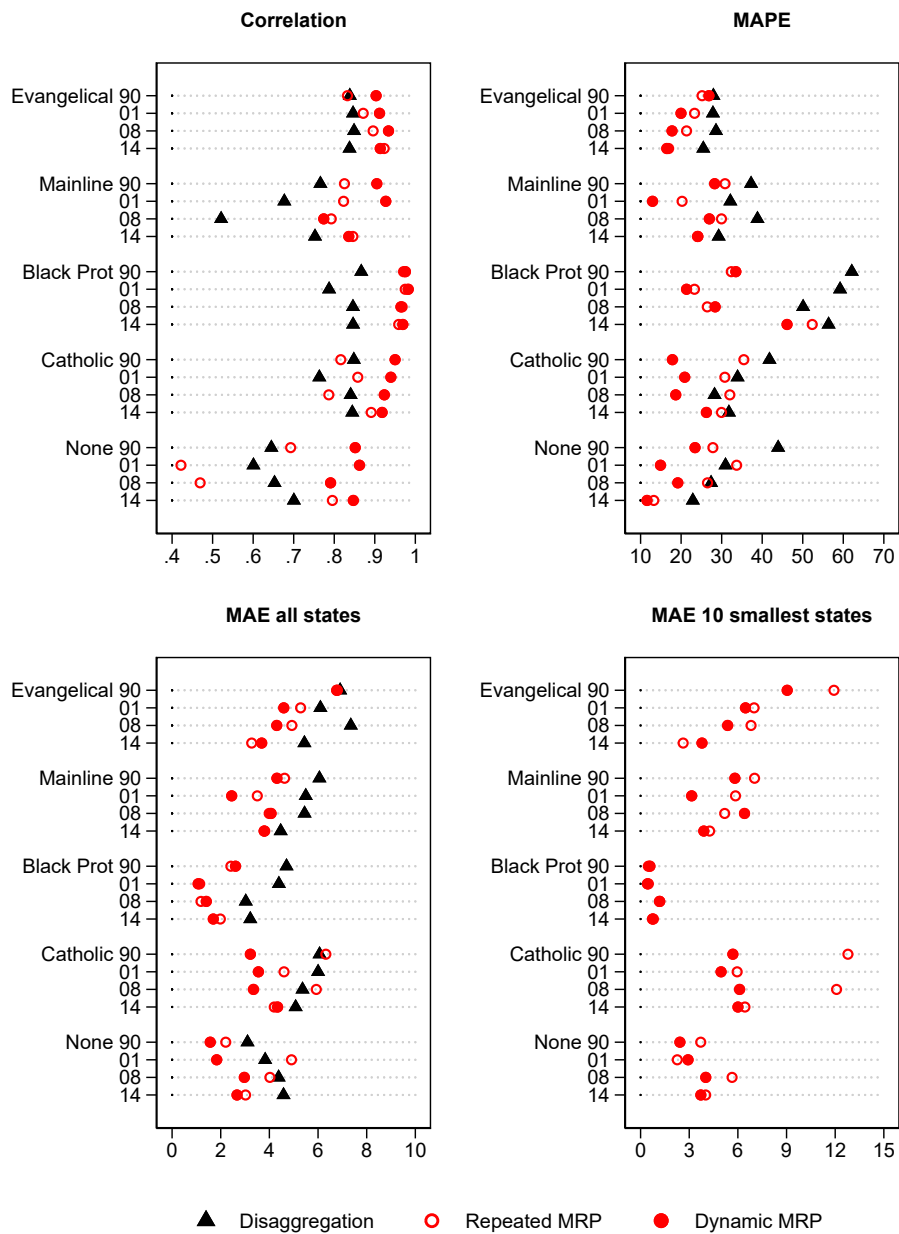


Figure 1: Comparisons of GSS-based estimates with external benchmarks: Religious affiliations. *Notes:* The reported statistics are based on all available estimates for a given year. Disaggregation provides estimates for 38 to 41 states per year. Repeated MRP and Dynamic MRP provide estimates for all 50 states and the District of Columbia. The bottom-right panel considers the 10 smallest states by population size other than Alaska, Hawaii, and the District of Columbia, which have been ignored to ensure consistent samples over time.

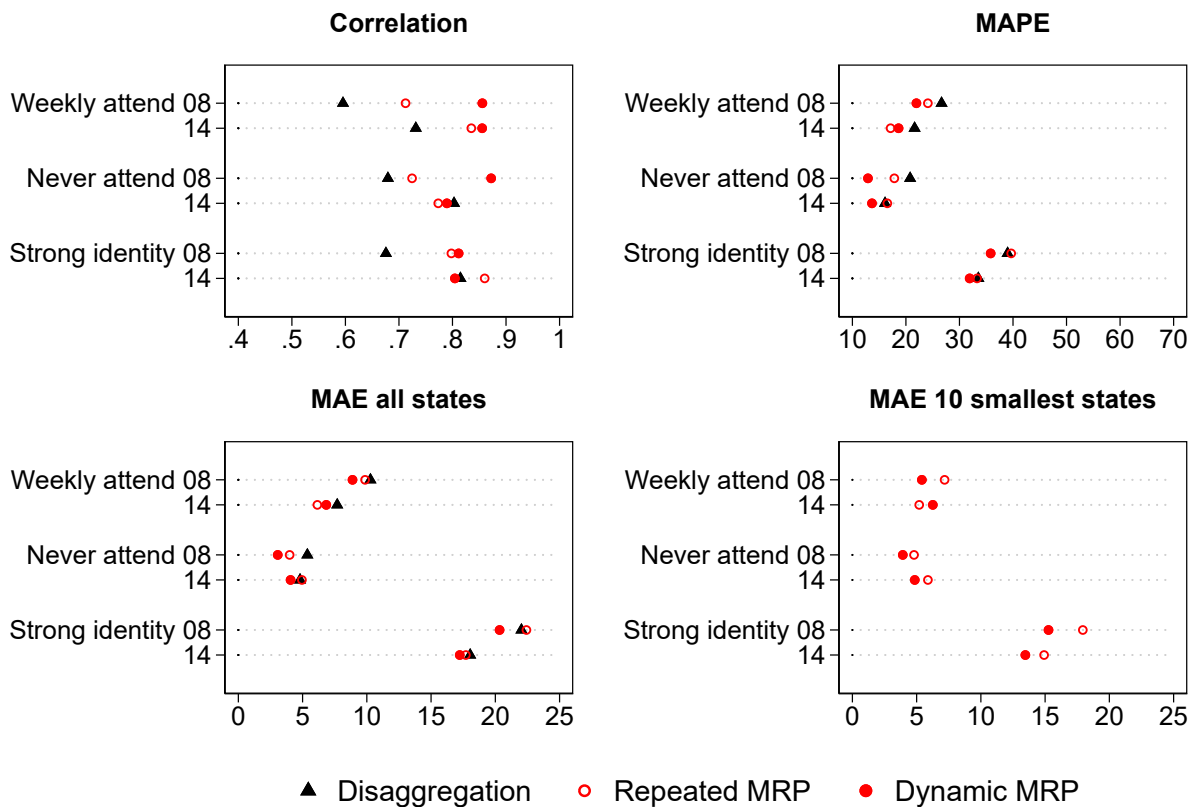


Figure 2: Comparisons of GSS-based estimates with external benchmarks: Frequency of religious service attendance and strength of identification. *Notes:* The reported statistics are based on all available estimates for a given year. Disaggregation provides estimates for 40 states in 2008 and 41 in 2014. Repeated MRP and Dynamic MRP provide estimates for all 50 states and the District of Columbia. The bottom-right panel considers the 10 smallest states by population size other than Alaska, Hawaii, and District of Columbia, which have been ignored to ensure consistent samples over time.

For more details, see Figures S1 to S4 in the online supplement, which plot our Dynamic MRP estimates against the external benchmarks, separately for different benchmark surveys, outcomes, and years.

As Figures 1 and 2 demonstrate, the Disaggregation estimates are convincingly outperformed by the Dynamic MRP estimates. Their benchmark correlations are lower in practically every case, whereas their MAPEs and MAEs are consistently larger. Many of the gaps are substantial: for example, whereas the correlation for religious nones in 2001 is 0.86 for Dynamic MRP, it is only 0.60 for Disaggregation. Turning to the Repeated MRP estimates, we observe that these generally also perform worse than their dynamic counterparts. Even though Repeated MRP gives better results than Disaggregation in most cases, Figures 1 and 2 show that further gains can be made by also partially pooling information over time, as Dynamic MRP does. Take again the example of religious nones in 2001, where Repeated MRP scores particularly poorly with a correlation of 0.42 vis-à-vis the 0.86 for Dynamic MRP.

Dynamic MRP has especially large payoffs for estimating outcomes for smaller states. If these states are identified at all in the GSS data, they only have a small number of observations in any given year (see Table S1 in the online supplement). In such cases, partially pooling information over time can strongly improve our estimates. Indeed, further analyses (not shown) reveal that for the largest 10 states by population size, Dynamic MRP and Repeated MRP yield almost identical estimates, with the Disaggregation method also performing reasonably well. For the smallest 10 states, on the other hand, many of the gaps between Dynamic MRP and Repeated MRP widen while there are no Disaggregation estimates available for these states to begin with (see the bottom-right panels of Figures 1 and 2).

Overall, our Dynamic MRP approach performs well—and substantially better than alternative methods—in terms of its predictive accuracy vis-à-vis external benchmarks, while also being more parsimonious than Repeated MRP, requiring only one multilevel regression for each outcome of interest. Furthermore, Dynamic MRP delivers more estimates than the other two methods, producing an estimate for each outcome in every state over the entire period 1973 to 2018. Disaggregation scores particularly poorly in this respect, as this method can only provide estimates for states where the GSS interviewed at least one individual. Yet, for each wave of the GSS, interviews are typically conducted in no more than 40 states, with most surveys up to 1983 only including 33 states (see Table S1 in the online supplement). Disaggregation thus leaves a large part of the American religious landscape unmapped.

To put the performance of our Dynamic MRP estimates further into perspective, we have taken advantage of the fact that there are several years for which we have multiple benchmark surveys available. This enables us to compare the external benchmarks against each other. Taking the PRLS as reference point for this exercise, we have examined the predictive accuracy of the ARIS estimates (for 2008) and the AVA estimates (for 2014). These comparisons demonstrate that the Dynamic MRP estimates perform as well as the ARIS and AVA estimates do in tracking the PRLS benchmarks and indeed frequently outperform them (see Figure S5 in the online supplement). This underscores that (Dynamic) MRP can provide a viable alternative to expensive, large-scale data collections if one is interested in measuring subnational outcomes.

The Rise of the Nones across States

Having verified the quality of our Dynamic MRP estimates, we now turn to the state-level trends that emerge from these estimates. Our focus is on how the rise of the nones has unfolded across states. Figure 3 displays these trends for all states together and by Census region.¹⁸

The most obvious observation from Figure 3 is that the share of religious nones has risen in each and every state between 1973 and 2018. Even in a highly religious state such as Mississippi—the state with the smallest share of nones in 2018—the share of nones has risen considerably, from 2.2 percent in 1973 to 11.8 percent in 2018. In other words, no state has been immune to the rise of the nones. Figure 3 also shows that the general trajectory is similar across most states, with the rise of

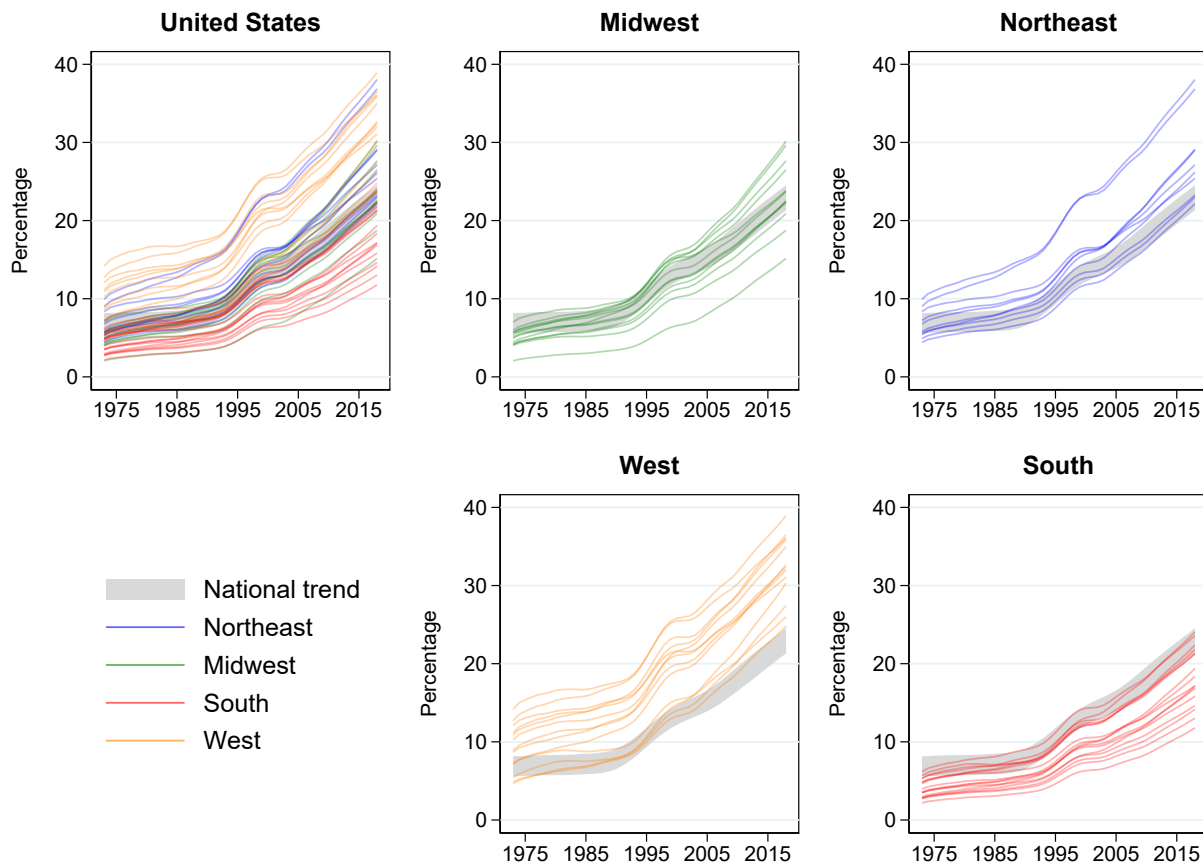


Figure 3: State-level trends in the share of religious nones based on Dynamic MRP, 1973 to 2018. *Notes:* The state-level trends have been smoothed using locally weighted regressions with a bandwidth of 0.2. The national trend has been smoothed using a locally weighted regression with a bandwidth of 0.4 and is plotted using the 95 percent confidence intervals around this smoothed trend. An interactive version of this figure is available at <https://dingemanwiertz.github.io/nonesFig3/>.

the nones really taking off from around 1990. Although the national trend displays a similar acceleration, our results indicate that various states already witnessed modest increases in their share of nones before 1990. This applies, among others, to Arizona (with a rise from 7.2 to 11.8 percent between 1973 and 1990), Minnesota (from 4.4 to 8.6 percent), and Washington (from 12.7 to 17.7 percent).¹⁹ Such early signs of the rise of the nones have so far gone largely unnoticed, with the national trend in the percentage of nones remaining relatively flat until 1990, only rising from 6.6 to 7.7 percent between 1973 and 1990.

Figure 3 additionally shows that the ranking of states in terms of their share of nones remains highly stable from 1973 to 2018, with a rank correlation of 0.87. However, there are multiple exceptions. Minnesota, for example, had a relatively high religious affiliation rate in 1973, ranking 15th across all states, yet had dropped to 38th place by 2018. By contrast, Florida climbed from position 24 to 14, now

being one of the more religious states in the country. These rank reversals point to a broader pattern, namely, that the magnitude of the changes varies substantially across states. Indeed, although several Southern states such as Alabama, North Carolina, and Tennessee experienced increases of less than 10 percentage points in their share of nones, various states in the Midwest (e.g., Michigan, Minnesota), West (e.g., Utah, Washington), and Northeast (e.g., Maine, Vermont) experienced increases of 20 percentage points or more. Overall, we observe that states that already started off with more nones have also experienced steeper increases in their share of nones: the correlation between initial levels and cumulative changes over the period 1973 to 2018 is 0.66. So, even though the share of religious nones has risen everywhere, we see growing gaps across states in religious affiliation rates, with the “poor” getting even poorer and the “rich” remaining relatively rich. Accordingly, the standard deviation of the share of religious nones at the state level has risen from 2.8 in 1973 to 7.0 in 2018.

Taking a closer look at the trends by Census region, we observe that most states in the Midwest and Northeast closely follow the national trend, both in their initial levels and the pace and timing of change. That said, several Midwestern states including Michigan, Minnesota, and Indiana are breaking away from the national trend in recent years, with above-average rises in their share of nones, whereas the Dakotas lag behind in comparison with the national trend. In the Northeast, Vermont and Maine have pulled away from other states in the region in the 1980s and nowadays are among the most secular states in the country. The West, in turn, emerges as the most secular region of the country, with most Western states scoring above the national average in terms of their share of nones throughout the entire period. This distinction has only become sharper in recent years. At the same time, we see that the West is marked by internal diversity, already from the 1970s: for example, the Northern Pacific states of Oregon and Washington are among the frontrunners nationwide when it comes to the rise of the nones, whereas more rural inland states such as Montana and New Mexico do not deviate much from the national trend. The South, finally, remains the most religious region of the United States, although also this region has become increasingly diverse internally. Whereas states in the “deep South,” such as Alabama and Mississippi, still have religious affiliation rates of close to 90 percent in 2018 (similar to the national average in the mid-1990s), many states in the northern part of this region (e.g., Kentucky, Maryland, Virginia) closely track the national trend, with religious affiliation rates of less than 80 percent in recent years.

To enrich our understanding of the rise of the nones across states, Figure 4 plots changes in the frequency of religious service attendance for different states against changes in their share of religious nones. We do this separately for weekly attendance (grouping together the GSS response categories “more than once a week,” “every week,” and “nearly every week”) and occasional attendance (grouping together the GSS response categories “2–3 times a month,” “once a month,” “several times a year,” and “once a year”). We focus on the period 1990 to 2018, as this is when most of the rise of the nones takes place.²⁰

The left panel of Figure 4 demonstrates that, with the exception of Mississippi, all states have witnessed a decline in weekly church attendance since 1990. For

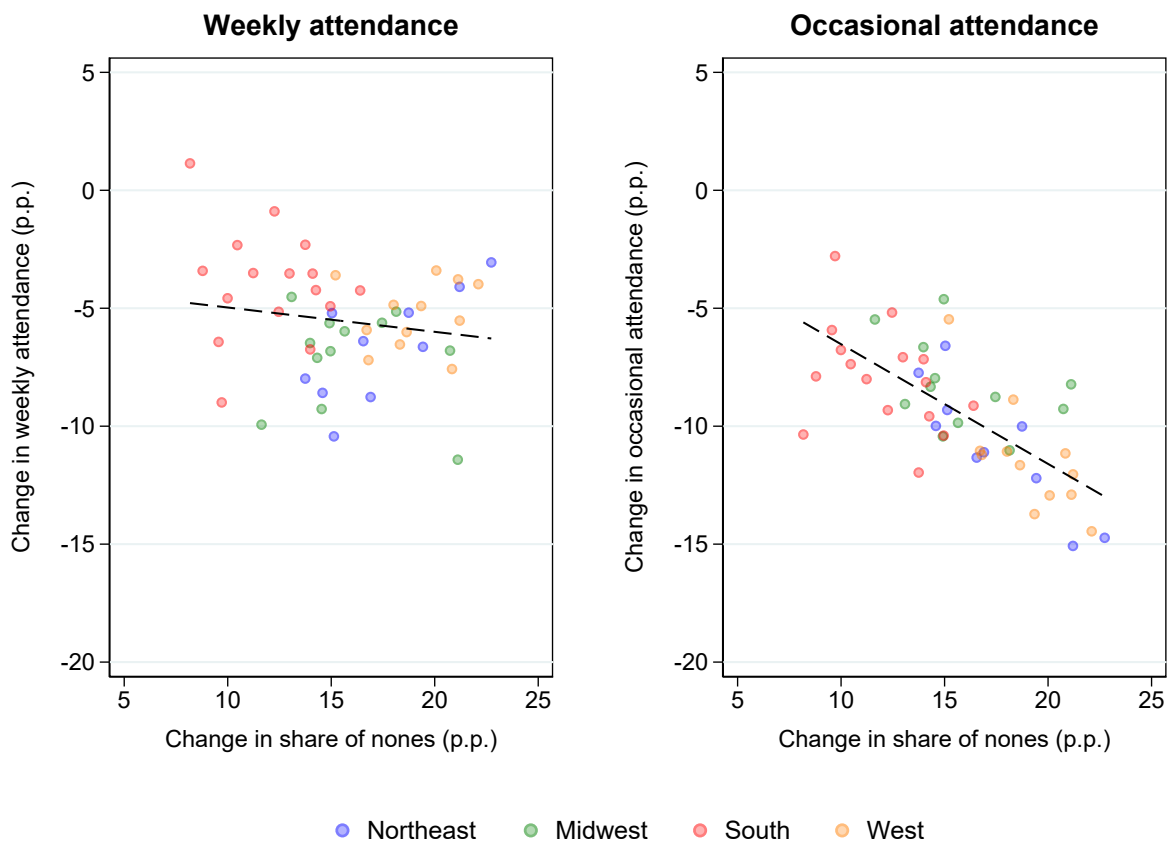


Figure 4: State-level trends in the share of religious nones and frequency of religious service attendance, 1990 to 2018. *Notes:* All axes are measured in percentage points (p.p.). The dashed lines depict the best-fitting lines. The correlation coefficient for the left panel equals -0.16 ; the correlation coefficient for the right panel equals -0.70 . Utah, as an outlier, has been omitted from both graphs; its coordinates are $(22, -17)$ for the left panel and $(22, 0)$ for the right panel. An interactive version of this figure is available at <https://dingemanwiertz.github.io/nonesFig4/>.

most states, the decline lies somewhere in the range of 0 to 10 percentage points. Midwestern and Northeastern states tend to experience bigger declines (e.g., -11.4 percentage points in Minnesota, -9.3 in Wisconsin, -8.8 in Massachusetts, -10.4 in Pennsylvania), whereas most Southern states are less affected (e.g., -0.9 percentage points in Arkansas, -2.3 in Oklahoma and West Virginia). Importantly, however, the strength of the decline in weekly attendance in a state seems unrelated to how much its share of religious nones has risen. That is, state-level changes in the share of nones have little to say about what has happened to intense religiosity at the state level.

The pattern looks different for occasional church attendance in the right panel of Figure 4. Here we see larger declines in attendance, for most states in the range of 5 to 15 percentage points. The Northeastern and Western states are more affected than the Midwestern and Southern states. Furthermore, this panel shows that

the increase in the share of nones in a state is highly predictive of the decline in occasional church attendance ($r = -0.70$). Although these results cannot be directly translated to the individual level, this strong correlation hints that new religious nones are primarily drawn from among moderate religious adherents, through disaffiliations being more common among weaker adherents or through religious involvement being less frequently passed on between generations in less religious families. In this respect, our results support the conclusions from earlier studies based on national data (e.g., Schnabel and Bock 2017; Voas and Chaves 2018).

A similar picture emerges from Figure 5, where we instead look at changes in the strength of religious identification. Looking again at the period 1990 to 2018, we distinguish between people who consider themselves to be “strong” adherents of their religion (left panel) and those who consider themselves to be “somewhat strong” or “not very strong” adherents (right panel).²¹ The left panel shows that declines in the share of the population with a strong religious identification have been limited, with several states even experiencing increases. Especially, various Southern states have an increasing share of “strong identifiers”—states such as Alabama, Arkansas, Mississippi, and Florida—whereas the largest declines occur in the Northeast. Nevertheless, any changes in the share of strong identifiers are only weakly related to changes in the share of religious nones.

Once again, the picture is different when we consider changes in the share of “moderate identifiers” in the right panel of Figure 5. This share has fallen across all states, with on average the largest declines in the West and the smallest declines in the South. We additionally observe a strong negative correlation with the change in the share of religious nones ($r = -0.83$): states with larger *increases* in their share of nones tend to have experienced larger *decreases* in their share of moderate religious identifiers. Hence, the rise of the nones seems to be taking place at the expense of moderate rather than strong religious adherents.

Together, the patterns in Figures 4 and 5 imply that the rise of the nones often brings about religious polarization, with stronger polarization in states where there is a bigger rise in nones. In those states, the combination of steep rises in the share of nones and a relatively resilient share of strong religious identifiers implies a “hollowing of the middle.”

Discussion and Conclusion

In this study, we examine state-level trends in key measures of religiosity between 1973 and 2018. In doing so, we refine our knowledge about religious change in the United States. Focusing on the share of Americans reporting no religious affiliation, we show that the rise of the nones, which has been well documented at the national level, is observed in each and every state. However, the strength of this trend varies significantly from state to state. We find larger increases in the share of nones in states that already had more nones to begin with. The result is religious divergence across states, with faster declines in religious affiliation in the Pacific West, New England, and some Midwestern states and slower declines in the Bible Belt and other parts of the Midwest. We also show how these state-level affiliation trends are linked to trends in other measures of religiosity. These analyses suggest

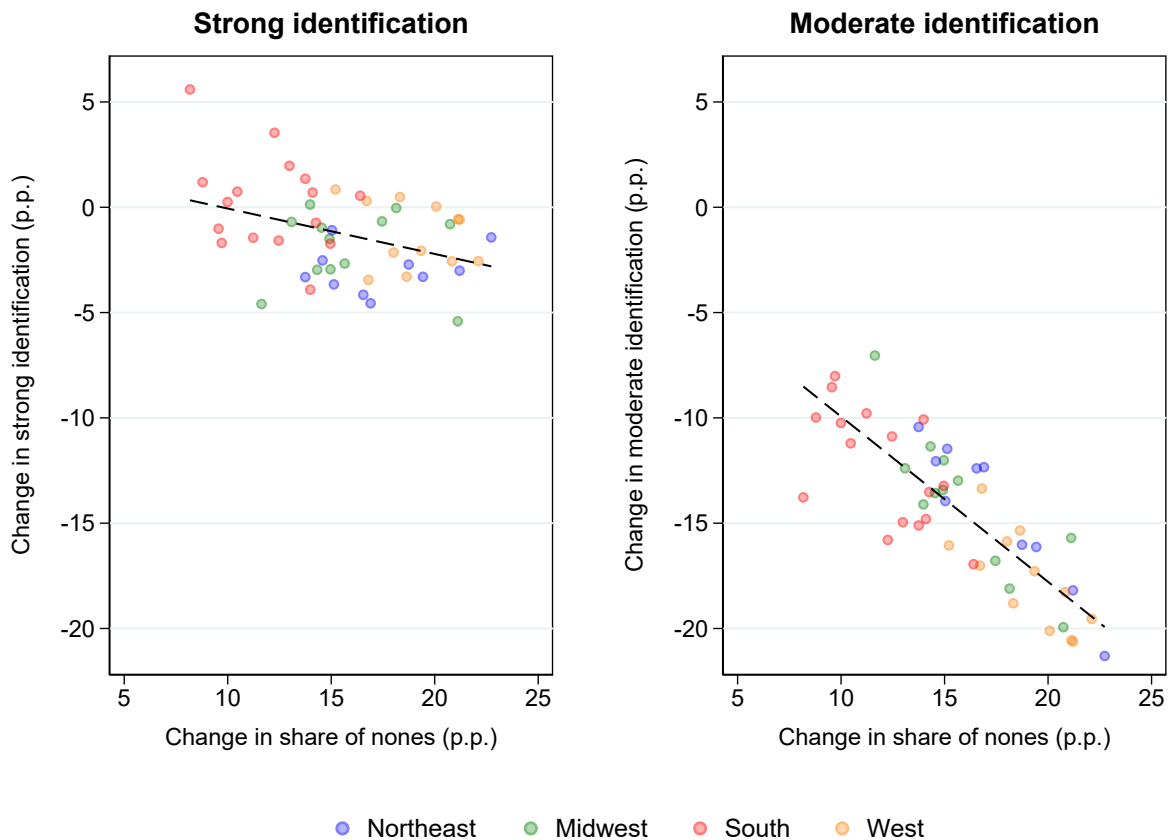


Figure 5: State-level trends in the share of religious nones and strength of religious identification, 1990 to 2018. *Notes:* All axes are measured in percentage points (p.p.). The dashed lines depict the best-fitting lines. The correlation coefficient for the left panel equals -0.38 ; the correlation coefficient for the right panel equals -0.83 . Utah, as an outlier, has been omitted from both graphs; its coordinates are $(22, -10)$ for the left panel and $(22, -13)$ for the right panel. An interactive version of this figure is available at <https://dingemanwiertz.github.io/nonesFig5/>.

that the rise of the nones has primarily taken place at the expense of moderate religious adherents, echoing earlier claims based on national data from, among others, Schnabel and Bock (2017) and Voas and Chaves (2018). Regular service attendance and strong religious identification, on the other hand, seem less affected by the rise of the nones, despite both outcomes displaying minor declines in most states over the study period.

There are multiple ways to interpret our finding of religious divergence across states. One possibility is that the observed divergence signifies that secularization is subject to social influence dynamics that give rise to a self-reinforcing process of religious decline. This would be in line with the secularization model, especially the model advanced by Voas (2009) and elaborated on by Voas and Chaves (2016) and Brauer (2018). The underlying idea is that leaving church or raising one's children secularly will be socially more acceptable in states where there are already

more religious nones, thereby fueling further increases in the share of nones in those states. Conversely, in relatively religious states leaving church may still be more of a taboo, translating into smaller increases in the share of nones. From this perspective, states may be in different phases of the secularization process, with states that already were less religious initially moving away from those that started off with more committed religious adherents.

However, if this interpretation is correct, the religious divergence in Figure 3 may just be a transitory phenomenon, which over time turns into a process of religious convergence, as the “early adopters” gradually dissipate their stock of moderate adherents that can be easily turned into nones, whereas for the “laggards” the bandwagon effects of secularization start to kick in.²² In support of this prediction, our analyses show that in *relative* terms the increases in the share of nones in more religious states are not any smaller than in more secular states. Moreover, all states appear to have relatively resilient contingents of strong adherents, which do not seem to dwindle quickly—and even may have grown in some states—in the face of rising shares of religious nones. This suggests that religious declines in more secular states may slow down over time, as their religious composition increasingly starts to represent a dichotomy of strong adherents versus religious nones.

In any case, at least over the period 1973 to 2018, we observe no religious convergence across states. This finding contradicts longstanding predictions that cultural differences between areas would fade under the influence of technological change and internal migration (e.g., McKinney and Bourque 1971). Indeed, in light of recent studies demonstrating the persistence of cultural differences between areas (e.g., Berger and Engzell 2019; Sequeira, Nunn, and Qian 2020), it remains questionable whether religious convergence is to be expected any time soon.

Aside from refining and updating our knowledge about the rise of the nones, this study also demonstrates the utility of Dynamic MRP for deriving estimates of subnational quantities from national surveys with limited sample sizes. By producing such estimates, Dynamic MRP opens up opportunities for addressing a wide range of new research questions, which require contextual measures of religious involvement over time. Comparisons of our Dynamic MRP estimates with external benchmarks indicate that Dynamic MRP can generate reliable estimates of state-level religious trends, even for states with only a few underlying observations, by partially pooling information across space and time and weighting the resulting estimates against the sociodemographic composition of the corresponding populations. More specifically, our Dynamic MRP estimates approach the external benchmarks about as closely as different external benchmarks approach each other. Our study thus extends the work of Gelman et al. (2018) and Claassen and Traunmüller (2020) in illustrating how Dynamic MRP expands the potential uses of nationwide surveys commonly used in social science research.

At the same time, we should keep in mind that (Dynamic) MRP delivers *estimates* of subnational quantities of interest, which are subject to uncertainty.²³ Researchers should therefore avoid interpreting Dynamic MRP estimates as “hard facts” and conduct sensitivity analyses and external validity checks where possible. This recommendation in fact applies more widely, as, for example, disaggregation of large-scale surveys like the ARIS or PRLS also provides estimates with uncertainty.

However, it is particularly pertinent in the case of Dynamic MRP because this approach has many “moving parts” or “researcher degrees of freedom” (Young 2018). Among other things, one has a choice as to which sociodemographic characteristics to account for in the poststratification stage, which area-level predictors to include in the multilevel regressions, how to model time trends, and whether to allow the influence of different predictors to vary across space or time. All of these choices may affect the resulting estimates.

For estimating time trends, the specification of the time-related components in the regression stage can be particularly influential. We have therefore examined how our estimates change when we allow for piecewise linear or quadratic trends as opposed to simple linear trends. As it turned out, this made little difference for our overall conclusions and the average predictive accuracy of our estimates, although it did make a noticeable difference for certain individual states (see Figures S6 to S9 in the online supplement). More generally, further refinements of our estimates certainly remain possible. Indeed, we regard our results as a first peek at what religious trends at the state level may look like, and we encourage others to replicate and improve upon our estimates. As the above discussion alludes to, there are various ways in which such improvements may be achieved. To name two additional examples, one might allow for correlated time trends across similar states (as is common in many electoral forecast models) or one might estimate the affiliation rates for different religious traditions via “nested multinomial MRP” instead of through a series of dichotomous MRP applications (see Kastle et al. 2015).

Focusing on the study of religious change in America, there are finally several ways in which our analyses can be extended, three of which we highlight here. First, it will be worthwhile to repeat our analyses for smaller geographic units such as counties. After all, our state-level analyses still leave a substantial amount of within-state variation unmapped, and county-level religiosity may represent a more proximate measure of religiosity in people’s immediate social surroundings. Descending to the county level, however, also brings additional challenges, including the availability of even fewer survey observations per area (although this simultaneously strengthens the case for applying Dynamic MRP) and a scarcity of external benchmarks to validate the resulting estimates against. A second extension involves deriving religiosity estimates for specific demographic groups such as age groups within each state. Our current analyses make no effort to separate out cohort- and age-specific trends, yet earlier research has demonstrated that such decompositions are helpful in illuminating the nature of any process of religious change (e.g., Voas and Chaves 2016). Third, by deriving area-level religiosity estimates, our study opens the door to systematic analyses of religious segregation in America—a topic that has so far received little attention despite its potential relevance in the context of broader debates about societal polarization and culture wars (e.g., Baldassarri and Park 2020; DellaPosta 2020; Finkel et al. 2020). We hope that scholars will take up these and other issues in future work, thereby further enriching our understanding of religious change in America and its implications.

Notes

- 1 Our full set of estimates and code to replicate our analyses are available at <https://github.com/dingemanwiertz/nones>.
- 2 The ARIS was fielded in 1990, 2001, and 2008, the PRLS in 2007 and 2014, and the AVA annually from 2013.
- 3 See Table S1 in the online supplement for statistics on the number of states and the number of respondents per state for each GSS wave.
- 4 For weekly attendance, we group together people who attend religious services “more than once a week,” “every week,” or “nearly every week.” For nonattendance, we combine people who attend religious services “never” or “less than once a year.” Strong identification is defined as whether people answer “strong” to the question, “Would you call yourself a strong X or a not very strong X?,” where X refers to their reported religious affiliation.
- 5 These four traditions together account for about 92 percent of all religious adherents in the GSS 1973 to 2018.
- 6 The frequency of data collection has fluctuated, but there is at least one survey every two years. We exclude 1972 from our analysis, as no identifiers for state of residence are available for that year. The model for strong religious identification additionally excludes 1973, as the underlying question was only first asked in 1974. We finally exclude the black oversamples for 1982 and 1987 for a total of 707 cases. See Table S1 in the online supplement for details about the total sample size, the number of states, and the number of cases per state for each survey wave.
- 7 See <https://github.com/dingemanwiertz/nones> for code to replicate our analyses.
- 8 See Table S2 in the online supplement for descriptive statistics for all variables included in our regressions.
- 9 We treat the District of Columbia as a state and group it together with the Northeastern states on this variable.
- 10 Black Protestant congregations have only been singled out in the 2010 wave of the RCMS. We have, therefore, given all other years the same value for the black Protestant congregational density variable.
- 11 We have also transformed the Republican vote share variable such that it is centered around 50 percent and measured in units of 10 percentage points.
- 12 Other specifications that we have experimented with include the use of random rather than fixed effects for the sociodemographic predictors and the estimation of time-varying effects of the sociodemographic and state-level predictors. Yet, once again, any improvements in model fit or predictive accuracy were negligible, whereas the added complexities often made matters worse. In this respect, our experiences echo those of Claassen and Traunmüller (2020) and Gelman et al. (2018), who conclude that increased modeling flexibilities may come at a cost.
- 13 For the 1980, 1990, and 2000 Censuses we use the five-percent IPUMS samples; however, for the 1970 Census only one-percent samples are available. As a result, we are unable to identify about 20 percent of all 6,528 respondent types (128 types \times 51 states) in the 1970 Census, compared with one to three percent for the other Census years. For the early 2000s we use the annual ACS samples (each covering about 0.4 percent of the U.S. population); for later years we use the then available five-year ACS samples (each covering about five percent of the U.S. population). Across the ACS years, the percentage of respondent types that we are unable to identify varies from 0.2 to about five percent.

Any respondent types that we cannot identify in the Census or ACS are assigned a relative population frequency of 0.

- 14 This selection of years is dictated by the availability of the benchmark surveys, with the ARIS being available for 1990, 2001, and 2008, the PRLS for 2007 and 2014, and the AVA annually from 2013 onwards.
- 15 The AVA distinguishes white evangelical, white mainline, black, Hispanic, and other nonwhite Protestants. We have assigned Hispanic and other nonwhite Protestants to the evangelical, mainline, or black Protestant tradition based on the prevalence of these traditions among Hispanic and other nonwhite Protestants in the 2014 PRLS.
- 16 Although the WTSSALL weight is not aimed at achieving representativeness at the state level, it does correct for the fact that only one adult in each household is interviewed (such that people living in large households are less likely to be interviewed) and for the two-stage nonrespondent subsampling design employed since 2004.
- 17 For estimation method m in year t , the MAPE and MAE of outcome X are calculated as follows (with s marking states):

$$MAPE_{m,t} = \frac{100}{51} \sum_{s=1}^{51} \left(\frac{|X_{m,t}^s - X_{benchmark,t}^s|}{X_{benchmark,t}^s} \right);$$

$$MAE_{m,t} = \frac{1}{51} \sum_{s=1}^{51} |X_{m,t}^s - X_{benchmark,t}^s|.$$

- 18 Interactive versions of Figures 3 to 5 are available online (see the notes to the figures for details). In these plots, one can highlight individual states and obtain more information about the underlying data points.
- 19 Although the precise magnitude of such changes for individual states depends on the specification of the underlying multilevel model, and especially the types of trends that are allowed for, the states that stand out are generally the same regardless of such specification issues. See also Figures S8 and S9 in the online supplement, which illustrate the estimated trends based on different time trend specifications.
- 20 Whereas the rates of weekly attendance are directly estimated using Dynamic MRP, our estimates for the rates of occasional attendance reflect the residual share of the population after subtracting our Dynamic MRP estimates for the shares of the population that attend religious services weekly or never.
- 21 The estimated share of people with a moderate identification is calculated as the residual share of the population after subtracting our Dynamic MRP estimates for the shares of the population that strongly identify with their religion or have no religion at all.
- 22 Baldassarri and Park (2020) observe similar dynamics of transitory polarization between Democrats and Republicans when it comes to views on moral issues. They find that both groups are gradually becoming more progressive, yet because Democrats adopt progressive views at a faster pace, the moral gaps between the two groups at first widen before narrowing later on when Republicans start to catch up.
- 23 We have generated estimates of the uncertainty around our Dynamic MRP estimates via simulation, by drawing 1,000 sets of coefficients and random effect predictions from each multilevel regression model (via the “arm:sim()” function in R), which we use to arrive at 1,000 estimates for each quantity of interest (e.g., the share of religious nones in Wisconsin in 2000). The empirical distribution of these estimates captures some of the uncertainty in our models. The resulting uncertainty estimates are available online as part of our full set of estimates (see endnote 1). It should be noted, however, that in

drawing the random effect predictions, we take the estimated variance of the random effect distributions as given. Our uncertainty estimates thus provide a lower bound for the true amount of uncertainty in our Dynamic MRP estimates.

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