JOURNAL FOR THE SCIENTIFIC STUDY OF RELIGION

Crafting Mosaics: Person-Centered Religious Influence and Selection in Adolescent Friendships

JIMI ADAMS
Department of Health & Behavioral Sciences
University of Colorado Denver

DAVID R. SCHAEFER
Department of Sociology
University of California Irvine

ANDREA VEST ETTEKAL
Department of Recreation, Park, and Tourism Sciences
Texas A&M University

This research addresses the intersection of two key domains of adolescents' lives: religion and peer networks. Religion scholars argue that religion is multi-faceted and better understood by focusing on combinations of indicators (i.e., mosaics), versus a variable-centered approach. We adopt this framework and investigate the interplay between religion and peer networks, both in how religious mosaics are shaped by friends and how religious profiles affect friend selection dynamics. With data from two schools in the National Longitudinal Study of Adolescent Health, we estimate religious mosaics using latent class analysis (LCA) to identify profiles consisting of combinations of commonly available survey-based measures of religious attitudes, behaviors, and identities. Finding evidence of theoretically expected profiles, we then use stochastic actor–based models (SABMs) to investigate network dynamics for these LCA-based religious profiles. We demonstrate how the profile data can be integrated within the SABM framework to evaluate processes of friend selection and influence. Results show evidence of adolescents influencing one another's religious mosaics, but not selecting friends on that basis.

Keywords: *adolescence, latent class analysis, religious mosaics, social networks, stochastic actor–based models.*

INTRODUCTION

Adolescence and early adulthood are key moments in the life course where religious attitudes, behaviors, and identities change (Pearce and Denton 2011; Smith and Denton 2005; Smith and Snell 2009). During adolescence, individuals increasingly take control over decisions about their religiosity, which is reflected in substantial shifts in their religious identities, behaviors, and the primary influences of those changes. For example, adolescents' religiosity has shown substantial declines (Regnerus and Uecker 2006; Uecker, Regnerus, and Vaaler 2007), other less linear changes (Pearce and Denton 2011), and the capacity to establish or alter the trajectories of other domains of life—for example, health (Ellison and Levin 1998; George, Ellison, and Larson 2002; Trinitapoli and Weinreb 2012), educational performance (Lehrer 1999; Regnerus 2000), and delinquency (Pearce and Haynie 2004). Adolescence is also a time when peers take on an

Acknowledgments: We thank participants at the 2014 INSNA and 2015 SSSR meetings for comments on previous iterations of this paper. This research was supported by the Eunice Kennedy Shriver National Institute of Child Health and Human Development, NICHD (R21-HD071885). We used data from Add Health, a project directed by Kathleen Mullan Harris and designed by J. Richard Udry, Peter S. Bearman, and Kathleen Mullan Harris at the University of North Carolina at Chapel Hill and funded by the NICHD (grant P01-HD31921), with cooperative funding from 23 other federal agencies and foundations. Information about how to obtain the Add Health data files is available on the Add Health website (http://www.cpc.unc.edu/addhealth). No direct support was received from grant P01-HD31921 for this analysis.

Correspondence should be addressed to jimi adams, Department of Health & Behavioral Sciences, University of Colorado Denver, 1201 5th Street, Denver, CO 80204. E-mail: jimi.adams@ucdenver.edu

Journal for the Scientific Study of Religion (2020) 59(1):39–61

increasingly central role in both influencing important behavioral and identity changes (Steglich, Snijders, and Pearson 2010; Veenstra et al. 2013), and providing the primary social groups wherein such changes manifest (Schaefer et al. 2011; Ueno et al. 2012). Given the intersection of religious changes and heightened importance of peers during the adolescent period in the life course, there is ample reason to expect that peer processes and religious changes shape one another in adolescents' lives (Cheadle and Schwadel 2012; Cook, Schwadel, and Cheadle 2017; Sepulvado et al. 2015).

Research on social networks has consistently found elevated similarity among peers on a wide range of behavioral and identity dimensions (McPherson, Smith-Lovin, and Cook 2001)—including religiosity (Cheadle and Schwadel 2012). This similarity can arise from a variety of social processes; here we focus especially on peer influence, wherein adolescents adopt behaviors similar to those of their friends (de la Haye et al. 2013; Haas and Schaefer 2014), and homophilous selection, a process whereby friendships are more likely to form between similar versus dissimilar peers (Schaefer, Kornienko, and Fox 2011). In light of the long-standing observation of such similarities, and the potential for similarity to arise through multiple social processes (Kandel 1978; Marsden 1988), scholars have sought to theoretically, methodologically, and empirically disentangle influence and selection processes from one another (Kossinets and Watts 2009; Steglich et al. 2010; Van Zalk et al. 2010). Although others have examined selection and influence on adolescents' religiosity (Cheadle and Schwadel 2012; Cook, Schwadel, and Cheadle 2017), we extend this by incorporating a recent fundamental reconceptualization of adolescent religiosity into this research.

Given the importance of religion in social life, researchers have devoted considerable attention to identifying the most appropriate way(s) of conceptualizing how religion matters in people's lives. Here, we follow the tradition initially developed in qualitative studies that aimed to capture how experiences of "lived religion" reflect the important dimensions of religion more faithfully than can strategies that conceptualize religion in terms of single variables (Ammerman 2007; McGuire 2008). Stemming from this literature, Lisa Pearce and colleagues demonstrated the capacity of in-depth religious surveys to capture some of religion's multidimensionality highlighted in the lived religion approach, by identifying what they label as religious "mosaics" (Pearce and Denton 2011; Pearce, Hardie, and Michael 2013). In brief, mosaics capture the ways *individuals* combine various religious behaviors and attitudes in patterned ways. We draw on this approach to use religious mosaics as the key conceptualization of religion when examining adolescents' peer influence and friend selection patterns.

In this paper, we begin by providing an overview of network research on selection and peer influence. We then discuss the motivation for conceptualizing adolescent religion as mosaics, and how selection and influence may play out for religious mosaics. We make the case that it is advantageous to combine these perspectives and illustrate their integration through a dynamic network model. Our data come from two large schools in the National Longitudinal Study of Adolescent Health ("Add Health"; Bearman, Jones and Udry 1997). We follow the mosaic approach by identifying adolescents' religious profiles, then estimate models of network and behavioral change (Snijders, van de Bunt, and Steglich 2010), to disentangle the effects of profile-based religious friend selection from influence. We discuss the implications of our findings for religious scholarship and identify pathways for advancing research on religion, networks, and their intersection using a mosaic-based approach.

Background

Adolescence and young adulthood is a time of rapid development, including changes in the ways individuals engage with and express their religious identities (Trinitapoli and Vaisey 2009; Uecker, Regnerus, and Vaaler 2007). Given this dynamism, and the wide range of domains to which religion is salient, researchers have devoted considerable time to explaining the sources of religious identification, behavior, and change during adolescence (Smith and Denton 2005). In particular, Cheadle and Schwadel (2012) combine this focus on adolescent religious change with recent advances in the statistical modeling of social network data to show how adolescent friendships reflect both religious influence between friends and friend selection based on religious similarities for a range of common religion variables. Our focus here is similar: we investigate how networks contribute to religious identity, but demonstrate how the assessment of this question can benefit from incorporating the perspective of religious mosaics (Pearce and Denton 2011; Pearce et al. 2013).

Network Processes in Adolescent Friendships

Few findings in the social sciences are as consistent as people's social contacts being highly structured to include others like themselves on a wide range of characteristics (McPherson, Smith-Lovin, and Cook 2001). This pattern of *assortativity* has been documented for relationships ranging from strong close personal connections (e.g., marital homogamy and best friends) to weaker ties, including infrequent acquaintances. In fact, it is now hard to find examples of behaviors or attributes for which this pattern does not hold (though marital relationships are more often heterogamous on one dimension—gender). As a small sampling from the vast range of relationship assortativity documented in the literature, friendships are similar on demographic attributes such as race (Goodreau, Kitts, and Morris 2009; Moody 2001), gender (Ridgeway and Smith-Lovin 1999), and age (Kossinets and Watts 2009); behaviors including substance use (Kirke 2004; Mercken et al. 2010), physical activity (de la Haye et al. 2011), and aggression/prosociality (Dijkstra et al. 2012); psychological states such as depression (Schaefer, Kornienko, and Fox 2011), or attitudes such as school attachment (Paxton and Moody 2002), antipathy (Berger and Dijkstra 2013), identities including school "crowds" (Brown, Von Bank, and Steinberg 2008), ethnic identity (Kornienko, Santos, and Updegraff 2014), sexual identity (Ueno et al. 2012), and religion (Cheadle and Schwadel 2012; Cook et al. 2017) and the list could go on; for a review see McPherson, Smith-Lovin, and Cook (2001).

Given the pervasiveness of assortativity, social scientists have long theorized its possible origins (Kandel 1978). When investigating the mechanisms responsible for assortativity, it is first necessary to take account of chance expectations. In particular, with any characteristic that is not equally distributed within a population, some level of relational homophily is to be expected simply by chance, which is known as baseline homophily (Blau 1977; Marsden 1988; McPherson, Smith-Lovin, and Cook 2001). The goal of network studies is often to measure and identify the processes responsible for observed levels of homophily that exceed these baseline levels (Kandel 1978). In general, behavioral similarity can arise via two distinct processes: individuals can adopt the behaviors of their peers—for instance, through peer influence—and/or friendships can form and dissolve in ways that maximize behavioral similarities—homophilous selection (Kandel 1978; Steglich et al. 2010). Here, we first show that adolescent networks show assortativity on religion in excess of baseline expectations, and then assess what processes account for the observed pattern.

Homophilous friend *selection* occurs when people form connections with others like themselves at rates greater than expected by chance (Kandel 1978). Homophilous selection can arise via numerous distinct mechanisms. For instance, McPherson and Smith-Lovin (1987) employ the notion of foci (Feld 1981) to explain how organizations such as voluntary associations or clubs can constrain relationship opportunities to others like oneself (Schaefer, Simpkins and Ettekal 2018). Alternatively, preferences for similar peers may lead people to select friends like themselves or, over time, dissolve friendships with dissimilar others (Van Zalk et al. 2010). Finally, network-based processes—for example, transitivity (the tendency of two individuals who share a friend in common to themselves form a friendship)—can amplify homophily by reinforcing relationships and friendship groupings (Snijders 2011; Wimmer and Lewis 2010). The nature of adolescent religiosity—as a collective and often organization-based activity (i.e., foci)—makes these processes relevant and suggests a high likelihood of observing adolescents selecting friends or maintaining friendships with those who are religiously similar to themselves.

Friendship assortativity also arises via peer *influence*, wherein over time individuals increasingly adopt behaviors or attitudes similar to those of their friends (Kandel 1978; Snijders 2011). Scholars have theorized the importance of peer influence for adolescents' behavioral change for decades on a wide range of outcomes (Kirke 2004; Van Zalk et al. 2010). Such influence can occur in many ways, often unintentionally, in light of adolescents' basic psychological need for relatedness (Deci and Ryan 2011). Over time, adolescents imitate their friends as they learn to relate with one another (i.e., social learning). Adolescents may also seek to be like their friends as a way of exploring their identities and "trying on" different roles, which may receive reinforcement from friends. Our interest is not so much in discerning how peer influence occurs, but rather, whether peer influence processes are also at work in the realm of religious mosaics. Early peer influence research has been criticized for focusing too heavily on problem behaviors and negative outcomes, while paying inadequate regard to peer influences on prosocial outcomes (Brechwald and Prinstein 2011). Recent studies have begun to address this limitation and offer evidence of peer influence on a broader set of outcomes, including emotions (van Workum et al. 2013), culture (Lewis and Kaufman 2018), and, most important for our purposes, identity (Kornienko et al. 2016; Rivas-Drake et al. 2017).

Combined, this literature leads us to expect that over time we should also see adolescents becoming increasingly similar to their friends in the domain of religion. This could occur through selection, peer influence processes, or both. Recent developments in the statistical modeling of network data (e.g., Snijders 2011; Snijders, van de Bunt, and Steglich 2010; Steglich, Snijders, and Pearson 2010) allow researchers to empirically disentangle the relative importance of influence versus selection. Religion scholars have applied these models to adolescents' religion (Cheadle and Schwadel 2012; Cook et al. 2017), finding evidence to support selection and influence. In light of these results, it is worth reconsidering how religiosity has been conceptualized in these studies and how well its measurement aligns with contemporary theorizing of adolescent religion.

Adolescents' Religious Mosaics

Before modeling network selection and influence, it is important to conceptualize and measure religion in a way that best reflects recent theorization of adolescent religion. Previous network scholarship demonstrates that measurement choices can substantially alter the capacity to identify and distinguish selection from influence effects. For example, in testing selection, Wimmer and Lewis (2010) demonstrate how homophily on race is better explained by using more precise measures of ethnicity versus broad racial categorizations. More pertinent here, studies of religion have found different selection and influence processes in operation depending on whether attitudinal, behavioral, or identity aspects of religion were measured (Cheadle and Schwadel 2012). Although different variables may in fact exhibit different selection and influence patterns, recent scholarship on adolescents' lived religious experiences suggest such variable-oriented approaches may not accurately capture the way religion is perceived and practiced. We therefore draw on Pearce and colleagues' application of these ideas in the concept of religious "mosaics" to reframe how adolescent religiosity should be incorporated into studies of religious selection and influence processes.

A growing body of literature advocates for a reconceptualization of religiosity away from variable-oriented notions, which have traditionally sought to succinctly capture the salient dimensions of people's religion with a single variable (or some limited set of variables). The weakness of such "variable centered" approaches, as documented in qualitative work focusing on "lived" or "everyday" religion, is that it does not reflect the ways that people experience and enact their religious identities to construct their own religious experience. As an alternative, the "lived religion" approach advocates that a more "person-centered" conceptualization of religion be used in research designs (Ammerman 2007; McGuire 2008). That is, for researchers to accurately capture religion as it is actually experienced requires describing the unique combinations of attitudes, behaviors, and identities in the way that individuals piece them together individually. In turn, once such profiles can be identified, the influence of religion on other aspects of one's life should be examined in relation to those combinations, rather than focusing on particular religious variables (Pearce et al. 2013).

Survey researchers have subsequently attempted to leverage these theoretical insights about combinatorial conceptualizations of individuals' religious experiences in ways that scale up for application to larger, more representative samples (Pearce and Denton 2011; Pearce et al. 2013). Descriptively, Pearce and colleagues use latent class analysis (LCA) to inductively estimate *mosaics* of religious profiles. Mosaics reflect the patchwork way that individuals combine varied religious dimensions into observable clusters. This work has then gone on to demonstrate how these mosaics provide additional leverage for explaining a range of behavioral outcomes (e.g., delinquency and academic performance), above and beyond the explanatory power available from the individual variables from which the mosaics were constructed (Pearce and Denton 2011). Here, we extend this approach further, by estimating profiles and examining their role in adolescent friendship dynamics.

Selection and Influence of Religious Mosaics

Our conceptualization of religious identity follows the religious mosaic approach described above. This approach moves beyond focusing on behaviors or attitudes singularly, given we have little reason to expect that individual variables form the basis on which peer influence and homophilous selection processes actually operate. In addition to the consistency with the conceptualization of religious mosaics, this shift to considering multiple measures in combination is also consistent with recent developments in network studies of selection and influence as well. These alterations have incorporated the recognition that behaviors and other attributes may operate in conjunction (Brechwald and Prinstein 2011:168).

For example, Strang and Soule (1998) argue that diffusion actually entails individuals "translat[ing] concrete practices into abstractions for export and then unpack [t]he abstraction into a (suitably modified) concrete practice upon arrival" (277). In other words, this perspective suggests that people do not directly mimic the behaviors of their peers, even when influenced by them. Instead, an abstraction actually diffuses, and is interpreted—by the person being influenced—at both the sending and receiving ends. This perspective is consistent with making religious mosaics the focus of investigating the way adolescents' religiosity and peer network processes are interrelated. To illustrate, it may be that while one adolescent's frequent religious attendance may not directly influence the attendance of their peers; but by signaling an identity of "highly religious" it may increase their peers' reported religious salience (or other dimensions). Lewis and Kaufman (2018) make similar claims about how homophilous selection operates not on individual traits, but on clusters of cultural tastes.

In sum, religious mosaics are more consistent with recent developments in conceptualizing and measuring religion, and therefore the estimation of network selection and influence processes should incorporate this approach into how they are modeled, rather than only testing them with variable-centered approaches. Thus, while prior studies of religiosity and network dynamics have separately examined variables such as denominational affiliation, importance of religion, service attendance, and prayer frequency, among others (Cheadle and Schwadel 2012; Cook et al. 2017), a mosaic-based conceptualization of adolescents' religion is readily adaptable into retheorized accounts of how selection and influence operates in dynamic peer networks. We assert that mosaics represent a more theoretically grounded means to capture adolescent religious experience and

Table 1: Descriptive statistics for sample school participants

	Jefferson HS $N = 502$	Sunshine HS $N = 891$
Demographics		
Gender (% female)	47.2	50.3
Race (%)		
White	94.4	3.8
African American	0	21.6
Hispanic	.8	39.2
Asian American	.6	23.9
Other	4.2	6.1
Age in years	15.4 (.99)	15.7 (.81)
Grade level	9.9 (.78)	10.5 (.50)
Religion		
Service attendance (1–5)	3.2 (1.44)	4.0 (1.19)
Importance (1–5)	3.5 (1.35)	4.3 (.98)
Prayer (1–6)	3.9 (1.84)	5.1 (1.42)
Religious Tradition (%)		
Evangelical Protestant	16.7	9.2
Mainline Protestant	32.2	16.8
Black Protestant	0	16.1
Roman Catholic	29.6	47.1
Other	3.6	5.8
None	17.9	5.1

Note: Unless otherwise noted, figures presented are means and (standard deviations).

therefore are the focus when evaluating network selection and influence processes. Thus, our primary research question is whether religious mosaics provide a basis for adolescents' friend selection and peer influence processes.

Data

We use data from the Wave I in-home and Wave II in-home surveys from the National Longitudinal Study of Adolescent Health ("Add Health"; Bearman, Jones and Udry 1997). Add Health contains information on complete networks for more than 100 schools at 1 wave, and 16 schools at 3 waves. Here, we focus on the two largest "saturated" schools with longitudinal complete network data.[1] These schools are of sufficient size to model friendship dynamics, while also reliably estimating school-specific religious profiles. The schools we use (frequently referred to by the pseudonyms "Jefferson" and "Sunshine" High School) represent two different social contexts. "Jefferson" is a mostly White school in the Midwest and "Sunshine" is a much larger, ethnically diverse school in the West; Table 1 provides descriptive overviews for each of

[1]Cheadle and Schwadel (2012) used network models with data from seven small Add Health schools to examine how readily adolescents influence and homophilously select friends separately for seven variables of religious identity (operationalized as affiliation, religious nones, and "born again" status), participation (prayer, service, and youth group attendance), and salience. They found evidence for selection and influence on each of these variables within their sample.

these schools on key study and contextual variables.[2] These schools have become common for benchmarking social network change estimation (Green et al. 2013; Haas and Schaefer 2014), in part because they represent such different contexts.

Measures

We construct religious profiles from measures in Add Health that (a) are commonly available across a variety of national surveys, and (b) capture the domains that provide the theoretical basis for religious mosaics as developed by Pearce and colleagues. This results in our profiles being constructed from three variables in Add Health—frequency of religious *attendance* (i.e., behavior),[3] religious *salience* (i.e., attitude), asked, "How important is religion to you?" (with Likert-scale response categories), and prayer frequency; descriptive statistics for these variables are included from Wave 1 for each school in Table 1. Given that the aim for including these indicators in our analysis is to mimic the theoretical motivation of Pearce and colleagues' approach as closely as is possible with Add Health data, we label it the "replicate" strategy.[4] In addition to this replicate approach, we use two alternative specifications to fit religious mosaics (described below).

We construct *friendship networks* from the nominations respondents provided for up to five male and five female friends within the school at each wave (Bearman et al. 1997). This contrasts with many studies that use proxy reports of alter behavior, which tend to suffer from self-projection bias (Vaisey and Lizardo 2010). In addition to the study's focal variables, we include a standard set of self-reported controls: gender (male is the reference category), age (in years at wave 1), race (non-Hispanic white = reference, non-Hispanic black, Hispanic, Asian, and other),[5] GPA, and parent's highest level of completed education. Jefferson is a smaller school, where adolescents nominated more friends than in the larger Sunshine, resulting in networks of much higher density. Over time, students in each school each nominated fewer friends (a common observation in longitudinal network studies; adams 2019). Transitivity did not change appreciably between waves, while Sunshine students seem to have reduced their nominations to exclude less close ties—as indicated by the increase in the reciprocity rate there across waves. The Jaccard index shows that these data are sufficiently stable for estimation with a stochastic actor–based models (SABM) (Snijders et al 2010).

Methods

We follow Pearce et al. (2013) by modeling religious mosaics with LCA to identify the profiles of combinations observed across the three primary religious variables described above. LCA is a person-centered approach to identifying subgroups in a population that combine behaviors/attributes in common ways. LCA is particularly appropriate here in that it allows for multiple dimensions of variation across the religious indicators included. This stands in contrast to approaches that would treat each variable individually (for the reasons described above), or

[2]Because of the needs of the SAB models described below, seniors at Wave I are excluded from our analyses as they are not observed at Wave II; this is the best practice according to Ripley et al (2013). The model imputes data for anyone else missing from our wave II (i.e., those lost through attrition).

[3]As with the measure used here, this is commonly limited only to attendance at weekend services.

[4]Our use of the term "replicate" should not be taken to mean that our analysis intends to replicate the analysis of Pearce and colleagues, with LCA solutions to be compared between them. Rather, we use this label to indicate our *approach* here follows theirs as closely as Add Health data allow.

[5]Race is only included in models for "Sunshine HS" because "Jefferson HS" is highly racially homogenous (see Table 1).

an index that would require assuming uniformity in how individuals combine these indicators (e.g., that increases/decreases in one component variable are equally likely or correlated with increases/decreases in another). This profile approach is consistent with the theoretical bases underpinning the search for religious mosaics (Pearce and Denton 2011; Pearce et al. 2013).

The basic form of the LCA model is

$$P(Y_i = y|X_i = x) = \sum_{l=1}^{n_c} \gamma 1 \prod_{m=1}^{M} \prod_{k=1}^{r_M} \rho_{mk|l}^{I(y_m = k)}, \tag{1}$$

which estimates the probabilistic class membership for each individual i, based on ρ (the probability of item response conditional on latent class) and γ (the probabilities of class membership). The first summation is over the number of classes, n_c. The first product is across question items M (here 3) and r_M, the number of possible responses for each item (five for our attendance and importance measures, and six for the prayer measure). That is, class membership is conditional on the probability of combining values across each included indicator in similar ways.

We use standard Akaike information criterion (AIC) and Bayesian information criterion (BIC) criteria to identify the best fitting number of classes (Linzer and Lewis 2014; McCutcheon 1987; Vermut and Magidson 2002). It is increasingly common to fold the identification of LCA classes and estimation of those classes association with outcome variables into a single model-fitting approach, rather than a "classify-analyze" approach that splits these into two separate modeling steps (Bray, Lanza Stephanie, and Xianming 2015). However, we use the classify-analyze approach here for two reasons. First, no modeling approach akin to the stochastic actor–based model for network dynamics that we employ (described below) is available to combine with the LCA fitting into a single model. Second, the classify-analyze approach is an acceptable procedure when class probabilities are high (e.g., $>.80$) (Jung and Wickrama 2008).[6] We use this classify-analyze approach to assign individuals to the class with the largest posterior probability, $Pr(C_i = k|Y_i)$, and then estimate network models using this nominal variable. Note especially that each indicator (*M*) can vary independently from the others, in a way consistent with the person-centered multidimensionality of religion as conceptualized by the mosaic approach. In practice, this allows for an exploratory analysis of the myriad possible combinations between these variables' response categories, reducing the sets in the output classes to correspond only with the prevalent combinations observed within the population.

We estimate a series of nested LCA solutions using the poLCA package in R (Linzer and Lewis, 2014). We use a variety of model fit indices to determine which model best replicates the data (i.e., G2 likelihood ratio, AIC, and BIC), which aligns with Pearce and colleagues' method. Our model uses the "replicate" set of variables described above: religious importance, religious attendance, and prayer frequency. With these variables, we estimate LCA solutions for two through six class solutions to empirically identify best-fitting class solutions. We estimate each LCA model separately at Wave I and Wave II for each school.

Alternate LCA Specifications

In addition to the replicate strategy described above, we also fit two alternative specifications for the LCA-model estimation of religious profiles. The first alternative replaces the measure

[6]The recommended strategy for including covariates in mixture models is to include covariates directly in the model, or in cases where this is not appropriate (e.g., the covariates produce substantial model instability), to use the class probabilities in subsequent models (Jung and Wickrama 2008). We were unable to estimate both the LCA and the subsequent models simultaneously; therefore, we estimated a parallel series of models using the class probabilities, but were unable to achieve convergence. We proceeded using the most likely class membership in subsequent models.

of prayer frequency with a measure that asks individuals to report on their denominational *affiliation* ("What religion are you?").[7] This variable—and the alternative specification using it—is important for three reasons. First, for studies not focused on religion, it is among the most common questions asked, and therefore among the most widely available variables on religion in social science research. Social scientific studies of religion frequently focus on measuring some combination of three dimensions: religious identity, behavior, and attitudes (Cornwall et al. 1986; Smith and Denton 2005). Furthermore, in practice these dimensions have most often been operationalized respectively with single variables: religious affiliation (i.e., denomination type), frequency of religious attendance (e.g., at weekly services), and self-identified importance (e.g., by asking how important one's religion is when making daily or important decisions—on a Likert scale). Only the first of these differs from the replicate approach described above. Despite some critiques of this variable-centered approach to measuring religion (Hadaway, Marler and Chaves 1993, 1998; Steensland et al. 2000),[8] the ubiquity of this approach to conceptualizing key measures of religion has led researchers to frequently incorporate measures reflecting these dimensions into a wide range of surveys, even when religion is not the project's focus.[9] As such, this specification addresses how readily this approach might be adaptable into other survey data where religion captures these more common dimensions.

Second, by substituting religious affiliation for prayer frequency, the combination of variables used to construct religious profiles brings the included variables more directly in line with the three dimensions of religion most commonly identified as important (Cornwall et al. 1986); religious affiliation aligns with the notion of religious "identity" not represented in any of the other variables described above. Drawing on these motivations, we label this first alternative LCA specification as the "canonical" approach. Specifically, this variable set adds religious affiliation to variables of service attendance and reported religious salience. We follow all other steps in the analytic approach exactly as described above for this canonical LCA profile specification. The canonical profiles provide a comparison to the replicate approach allowing us to ask how readily religious mosaic profiles are estimable from limited religious information, particularly the variables most commonly available in studies not focused on religion. Comparing the network results across these two strategies also addresses how similarly the approach developed here could be expected to operate similarly in other research where only one or the other combination of variables are possible.

The third importance of the religious affiliation variable is that, unfortunately, Add Health employed a skip pattern wherein anyone who reported no religious affiliation was not subsequently asked the rest of the religious questions. This constrains our ability to capture as full a range of profiles as would be available from more complete data. We discuss the implications of this limitation in the "Results" section when comparing our LCA classes to those of Pearce and colleagues. Moreover, because of this skip pattern, we knew in advance that we would not be able to fully replicate the class solutions identified by Pearce and colleagues. That is, while Pearce and colleagues find five-class solutions, one of theirs was not identifiable with Add Health data.[10] As such, to draw—somewhat *a priori*—on their findings (while above we follow their

[7]We recode the denomination variable into the "religious tradition" (reltrad) summary categories that have become common practice in the religion literature (Steensland et al. 2000). We also fit the profile results using the raw denomination variable, and found similar results to those produced with reltrad. Given the lack of difference, we opted to follow the more parsimonious literature standard for this measure.

[8]The lived religion approach described above was developed in part as a means to overcome some of these very critiques.

[9]In addition to the National Longitudinal Study of Adolescent Health that is our focus, similar variables are available in the National Survey of Family Growth, National Longitudinal Survey of Youth, and the Health and Retirement Survey, and numerous others.

[10]The "Avoider" class includes individuals who do not strongly identify with (a single) religious tradition, but nonetheless are not irreligious (Pearce and Denton 2011; Pearce et al. 2013). Given that unaffiliated individuals were not asked the

Table 2: Network descriptive statistics

	Jefferson HS		Sunshine HS	
	Wave I	Wave II	Wave I	Wave II
No. of ties	1,721	1,345	1,381	1,014
Density	.007	.006	.002	.002
Outdegree mean (standard deviation)	3.43 (2.21)	2.67 (2.18)	1.55 (1.66)	1.14 (1.51)
Jaccard	.269		.240	
Reciprocity	.446	.457	.354	.411
Transitivity	.207	.214	.232	.263
LCA-class assortativity (OR)	1.32^{***}	1.25^{***}	1.16^{***}	1.20^{***}

$^{***}p < .001$.

Note: Numbers are for the specified network, except outdegree (which are the mean and standard deviation across individuals in the network) and assortativity (odds ratio).

methods), we also extract the 4-class solution using the "replicate" variables that conceptually align with Pearce and colleagues.[11] We label this second alternative specification as the Rep4 (4-class replicate LCA solution).

Fitting the LCA Solutions in a Stochastic Actor–Based Model

Once class assignments have been made, we use these to examine religion-friendship dynamics. Table 2 demonstrates the presence of assortativity on the LCA-class memberships,[12] which is what we seek to explain here. We use an SABM, with religious selection and influence on latent class membership as the key parameters of interest. An SABM allows for the simultaneous modeling of changes in network and attribute data. These models can address the central aim here—separating peer influence from homophilous selection, while also properly accounting for the interdependence between network observations (which would not be possible with, for example, logistic regression), and controlling for endogenous network processes (e.g., tendencies toward reciprocity and triadic closure, described in more detail below). The SABM involves maximization over two separate functions representing network selection and behavior change (i.e., religious measures). First, the network function estimates effects that shape the likelihood of tie presence or absence, and takes the form:

$$f_i(\beta, x) = \sum_k \beta_k s_{ki}(x) + \varepsilon(x, z, t, j), \qquad (2)$$

where $f_i(\beta,x)$ is the value of the network function for actor (i) with respect to all potential alters (j), given the current set of parameter estimates (β) and state of the network (x), for k effects,

other religion questions in Add Health, this class is unidentifiable in our data. However, all four of the other classes could *potentially* be identified from the Add Health variables.

[11]This particular solution differs from the procedure described above in that we ignore the fit statistics for determining the optimal number of classes identified in the data. Instead we force a 4-class solution to see if the four classes that would have been identified correspond to the set from Pearce et al.'s findings that are available to us, given the limitations available in these data.

[12]We report assortativity as computed by the α segregation index (Moody 2001) for each school and wave, using the "replicate" 3-class solution. Other specifications are similarly assortative.

represented as s_{ki}, which may be based on the network (x) and individual attributes (z). In addition, the model incorporates some random disturbance (ε) associated with each of x, z, t, and j. The key effect of interest in the network function here is homophily on religion. Homophily effects estimate how likely individuals are to nominate someone who is more similar on religiosity versus someone who is more dissimilar. For the categorical measures (e.g., LCA class), we use the *same* effect, which codes dyads as 1 if their scores match, and 0 otherwise. For the continuous indicators (prayer, attendance, and importance), we use the *similarity* effect, which is a transformation of the absolute value between scores for two dyad members. This effect ranges from 0 (greatest dissimilarity) to 1 (identical scores) across dyads. For the continuous measures, we also included related effects for how religiosity affects the tendency to send (*ego* effects) and receive (*alter* effects) ties.

Several other effects were included in the model to control for selection based on other individual attributes (i.e., sex, grade, and SES), dyadic attributes (extracurricular activity and course overlaps), and network processes. Important network processes to include as controls in these models are reciprocity (the tendency for individuals to send ties to those who they currently receive ties from), transitivity (the tendency for individuals who share a friend in common to have an elevated chance of themselves becoming friends), and popularity effects (the "Matthew effect" of disproportionately connecting to those already having higher numbers of friends). A final set of controls captures the "foci" of opportunities for friendship formation described above—those indicating which adolescents participated in the same extracurricular activities and courses (Schaefer et al. 2011). In combination, these effects represent how likely i is to select j (i.e., add a new tie to j or maintain an existing tie to j).

Second, the behavior objective function takes a similar form:

$$f_i^z(\beta, x, z) = \sum_k \beta_k^z s_{ki}^z(x, z) + \varepsilon(x, z, t, \delta), \tag{3}$$

where $f_i^z(\beta, x, z)$ is the value of the behavioral objective function for actor (i) for behavior (z), and all other elements are as in Equation (2), with the exception of δ, which is the error associated with behavior *change*.[13] The key effect here is peer influence on religion, which captures whether friends are more likely to become (or remain) more religiously similar over time than adolescents who are not friends. Additional effects in these models controlled for the effects of race, sex, age, SES, parent's religiosity, and two-parent family on level of religion.

Estimating the peer influence effect in the behavior function requires a different specification for continuous versus categorical religion measures. For continuous religion measures, we use the behavior function shown in Equation (3) and measured peer influence with the *total similarity* effect. Total similarity was calculated as the sum of the absolute differences between ego's score and the scores of the friends nominated by ego. The sum was reverse-coded and centered based on the average level of similarity across all dyads (Ripley et al. 2013).

For categorical religion profiles that result from LCA, we specify religious classes in the behavior function using a two-mode network (Snijders, Lomi, and Torló 2013). In the two-mode representation, adolescents have a score for each class (or category of affiliation), with a "1" coded for the class they were assigned to, and a "0" coded for all other classes. The key predictor in this part of the function is the number of friends who belong to each category or class of religion. Thus, the likelihood of choosing each category of the religious profiles is determined by the number of friends who made that same choice. We controlled for how youths' sociodemographic

[13] We should note that the language of "behavior function" is that of the general SABM approach. Here, we are not modeling a "behavior" but a cluster of religious indicators. We maintain the language of "behavior" here in the "Methods" section merely for consistency with the SABM literature.

characteristics affected their religious choice by including interactions between dummy variables representing classes and each sociodemographic control variable. We also included dummy variables for all classes except one in order to control for the overall probability of belonging to each class.

In addition to the effects described above, models also include a series of standard network structural controls: reciprocity, transitivity, an interaction between reciprocity and transitivity, 3-cycles (nonhierarchical triad closure), actors at distance-2 (an indicator of the lack of triad closure), indegree–popularity (how number of incoming ties affects the likelihood of receiving future ties), outdegree–popularity (how number of outgoing ties affects the likelihood of receiving future ties), and indegree–activity (how number of incoming ties affect the likelihood of sending future ties). These latter three measures were transformed using a square root function to give greater weight to differences at lower levels of degree.

Alternate SABM Specifications

Although our focus is on the SAB models that allow us to estimate mosaic-based religious selection/influence, we also estimate a series of preliminary models examining the same patterns for each of the individual variables with which the LCA profiles are constructed. These allow us to (1) be sure our models are properly calibrated to reproduce similar results on this set of variables in previous work (Cheadle and Schwadel 2012; Cook et al. 2017), and (2) to show where their results diverge from those in our proposed approach. Those preliminary models include: (1) four separate SABM specifications, one for each of the individual variables used across the replicate and canonical LCA estimations, and (2) a single composite model including all four variables into a single model. In addition to these preliminary models and the SABM of primary interest—using the best fitting LCA solution from the replicate class variable—we also specify SABMs for each of the alternate LCA specifications described above (the canonical variable set and the 4-class solution with the replicate variable set).

Results

Identifying Latent Classes of Religiosity Among Adolescents

We estimated a total of four separate LCA models (two schools, by two waves of data) for the replicate and each alternative specification. All model fit statistics are shown in Table 3. When using the replicate variables, in each school, across both waves, the 3-class solution had the lowest BIC (Nagin 2005).[14] Thus, we examined the class probabilities to determine whether the class probabilities were high enough to proceed using the classify-analyze approach for these three classes. All class probabilities were $>.80$ for the 3-class solutions, but fell below this cut-off when adding additional classes. Therefore, we chose the 3-class solution to interpret as the model demonstrating best fit to the data. In what follows, we discuss the findings primarily only as they relate to this 3-class replicate LCA solution, and mention the alternate specifications only where they differ substantially from those.

Three Classes of Religiosity

Table 4 shows the posterior response probabilities for each school, by class solutions, for each set of variables at Wave 1.[15] Using the replicate set of variables (i.e., attendance, importance,

[14]However, using the replicate variables, it is worth noting that the 3-class solution had better fit over the 4-class solution by only a small margin.

Table 3: Fit statistics for LCA models

	Wave 1				Wave 2			
	G^2	BIC	AIC	Range of Avg. Class Probabilities	G^2	BIC	AIC	Range of Avg. Class Probabilities
				Jefferson High School				
Replicate variables[a]								
Two classes	423.95	4,693.47	4,568.48	1.00–1.00	397.70	3,731.59	3,619.24	1.00–1.00
Three classes	**131.26**	**4,494.74**	**4,303.79**	.84–1.00	**143.14**	**3,563.29**	**3,392.68**	**.42–1.00**
Four classes	47.27	4,502.42	4,247.80	.69–1.00	79.15	3,585.56	3,356.69	.56–1.00
Five classes	26.31	4,559.36	4,254.84	.55–1.00	44.86	3,637.52	3,350.40	.46–1.00
Six classes	12.96	4,635.82	4,269.50	.42–1.00	44.85	3,723.78	3,378.40	.38–1.00
Canonical variables[b]								
Two classes	218.40	4,388.20	4,269.04	1.00–1.00	180.41	3,487.77	3,375.42	1.00–1.00
Three classes	**85.05**	**4,344.65**	**4,163.69**	**.81–1.00**	**80.76**	**3,474.37**	**3,303.76**	**.73–1.00**
Four classes	57.98	4,407.36	4,164.62	.63–1.00	45.50	3,525.37	3,296.50	.55–1.00
Five classes	44.03	4,483.20	4,178.67	.57–1.00	29.66	3,595.79	3,308.67	.54–1.00
Six classes	35.78	4,564.74	4,198.42	.45–1.00	19.69	3,672.07	3,326.69	.44–1.00

(Continued)

Table 3: *(Continued)*

	Wave 1				Wave 2			
	G^2	BIC	AIC	Range of Avg. Class Probabilities	G^2	BIC	AIC	Range of Avg. Class Probabilities
				Sunshine High School				
Replicate variables[a]								
Two classes	541.36	8,339.11	8,200.93	1.00–1.00	468.86	5,919.74	5,792.13	.88–.97
Three classes	**125.05**	**8,022.45**	**7,812.61**	**.85–1.00**	**143.65**	**5,688.69**	**5,494.92**	**.79–1.00**
Four classes	56.33	8,053.38	7,771.89	.71–1.00	57.46	5,696.68	5,436.74	.61–1.00
Five classes	33.99	8,130.69	7,777.55	.62–1.00	44.21	5,777.59	5,451.48	.56–1.00
Six classes	21.23	8,217.59	7,792.79	.56–1.00	25.09	5,852.64	5,460.37	.44–1.00
Canonical variables[b]								
Two classes	297.52	8,723.31	8,585.12	1.00–1.00	299.24	6,179.74	6,052.07	1.00–1.00
Three classes	**104.05**	**8,629.48**	**8,419.64**	**.80–1.00**	**120.43**	**6,097.00**	**5,903.15**	**.77–1.00**
Four classes	54.30	8,679.39	8,397.90	.62–1.00	68.16	6,138.95	5,878.88	.64–1.00
Five classes	37.58	8,762.32	8,409.18	.49–1.00	51.89	6,216.88	5,890.61	.61–1.00
Six classes	22.36	8,846.75	8,421.95	.41–1.00	37.93	6,297.12	5,904.64	.50–1.00

Note: Values in bold indicate best-fitting model. G^2, likelihood ratio test statistic; BIC, Bayesian information criterion; AIC, Akaike information criterion.

[a]"Replicate Variables" indicates the solutions using variables consistent with the conceptual model employed by Pearce and colleagues—that is, limited to behavioral and attitudinal variables. Here that includes religious importance, religious attendance, and prayer frequency.

[b]"Canonical Variables" replaces prayer frequency in the "replicate" set with religious affiliation to match the limited set of variables most often available in surveys not primarily concerned with religion.

Table 4: Posterior response probabilities (rhos) for LCA class solutions at wave 1

	Affiliation (%)[a]									
	NR	EP	MP	BP	RC	OT	Attendance M (SD)[b]	Importance M (SD)[b]	Prayer M (SD)[c]	% of Sample[d]
Jefferson High School ($N = 502$)										
Total	17.91	16.70	32.19	.00	29.58	3.62	3.20 (1.44)	3.46 (1.35)	3.94 (1.85)	
3-Class LCA, Replicate variables[e]										
I							1.00 (.00)	1.00 (.00)	1.00 (.00)	15.32
II							4.55 (.73)	4.52 (.50)	5.46 (.64)	29.72
III							2.92 (.76)	3.54 (.70)	3.81 (1.36)	54.95
3-Class LCA, Canonical variables[f]										
I	100.0	.00	.00	.00	.00	.00	1.00 (.00)	1.00 (.00)		15.32
II	.00	32.26	32.90	.00	31.61	3.23	4.83 (.37)	4.54 (.50)		24.97
III	.00	13.04	43.08	.00	38.74	5.14	2.98 (.76)	3.66 (.74)		59.71
4-Class LCA, Replicate variables[e]										
I							1.00 (.00)	1.00 (.00)	1.00 (.00)	15.32
II							4.66 (.77)	4.65 (.48)	5.58 (.53)	23.91
III							2.70 (.73)	2.80 (.72)	2.38 (.70)	9.91
IV							3.27 (.85)	3.89 (.38)	4.54 (1.06)	50.86

(Continued)

Table 4: *(Continued)*

	Affiliation (%)[a]									
	NR	EP	MP	BP	RC	OT	Attendance *M* (*SD*)[b]	Importance *M* (*SD*)[b]	Prayer *M* (*SD*)[c]	% of Sample[d]
Sunshine high school ($N = 891$)										
Total	5.10	9.17	16.76	16.08	47.11	5.78	4.02 (1.19)	4.32 (.98)	5.05 (1.42)	
3-Class LCA, Replicate variables[e]										
I							1.00 (.00)	1.00 (.00)	1.00 (.00)	3.59
II							4.51 (.78)	4.69 (.47)	5.67 (.65)	79.14
III							3.07 (.81)	3.82 (.63)	3.92 (1.21)	17.27
3-Class LCA, Canonical variables[f]										
I	100.0	.00	.00	.00	.00	.00	1.00 (.00)	1.00 (.00)		3.59
II	.00	10.57	17.79	18.62	46.48	6.54	4.57 (.78)	4.78 (.41)		74.36
III	.00	7.44	17.36	12.81	57.44	4.95	3.23 (.79)	3.79 (.49)		22.06
4-Class LCA, Replicate variables[e]										
I							1.00 (.00)	1.00 (.00)	1.00 (.00)	3.59
II							4.61 (.74)	4.78 (.42)	5.66 (.65)	72.38
III							3.58 (.61)	4.01 (.29)	4.78 (1.11)	17.69
IV							2.41 (.66)	3.55 (.86)	3.52 (1.52)	6.34

[a]NR = no religious affiliation; EP, evangelical Protestant; MP, Mainline Protestant; BP, Black Protestant; RC, Roman Catholic; OT, Other.
[b]Range = 1–5.
[c]Range = 1–6.
[d]Sample percentages based on predicted class membership by modal posterior probability.
[e]"Replicate variables" indicates the solutions using variables consistent with the conceptual model employed by Pearce and colleagues—that is, limited to behavioral and attitudinal variables. Here that includes religious importance, religious attendance, and prayer frequency.
[f]"Canonical Variables" replaces prayer frequency in the "replicate" set with religious affiliation to match the limited set of variables most often available in surveys not primarily concerned with religion.

and prayer), the three classes were qualitatively and quantitatively distinct, following a similar pattern across schools and waves. The smallest class in both schools (i.e., Class 1) comprised adolescents who were not religious, that is, did not identify with any religious tradition. As noted above, because of Add Health skip patterns, these individuals were *assumed* to not attend religious services, pray, or attribute any importance to religion. The other two classes were quantitatively distinct. Adolescents in Class 2, the largest class in Sunshine High School (79.1 percent of the sample), were highly religious (i.e., attended services and prayed frequently and rated religiosity as fairly important), whereas adolescents in Class 3, the largest class in Jefferson High School (54.9 percent of the sample), were moderately religious (i.e., attended services and prayed fairly infrequently and rated the importance of religiosity as neutral).

Using the alternative specification with the "canonical" set of variables (i.e., importance, attendance, and affiliation), the best-fitting model was also a 3-class solution. The three classes included adolescents who: (1) had no religious affiliation, (2) were very religious—about equally divided across religious affiliation (but, notably more evangelical Protestants than the third class), rated religiosity as very important, and attended services frequently, or (3) were moderately religious (largely Mainline Protestant or Roman Catholic), rated religiosity as fairly important, but attended services comparatively infrequently.

In the second alternative specifications, we examined the 4-class solution using the replicate variables to determine whether Pearce and colleagues' classes could be replicated. As noted above, this was not the best-fitting solution for the "replicate" set of variables, so these results should only be interpreted in light of how they align with Pearce and colleagues' findings, and not as a primary assessment of our research questions here. The 4-class solution included the same not-at-all and highly religious classes as identified in the3-class solutions. But how the "moderate" classes differed from those extremes varied across the schools. First, there was a moderate class identified in each school that was relatively consistent across all indicators. However, in Jefferson, this class reported only slightly higher importance, prayer, and attendance than the irreligious group (akin to the "Avoider" class identified by Pearce and colleagues). In Sunshine, the overall level of religiosity is higher than in Jefferson, and this "consistently moderate" class is much closer to the highly religious class, lagging only slightly behind them across all three indicators. The fourth class in each school combines reporting religion as relatively important and relatively frequent prayer, but reports only modest participation in religious services. This final class, while not exactly matching the distributions, approximates some characteristics of the "Adapters" class identified by Pearce et al. (2013)—those combining differing levels of religiosity across indicators. This suggests that while this solution is not the best fit to Add Health data, the substantive patterns here are suggestive that combinations here, as in Pearce et al. (2013), are not simply coordinated levels of religiosity that operate in lockstep across each indicator.

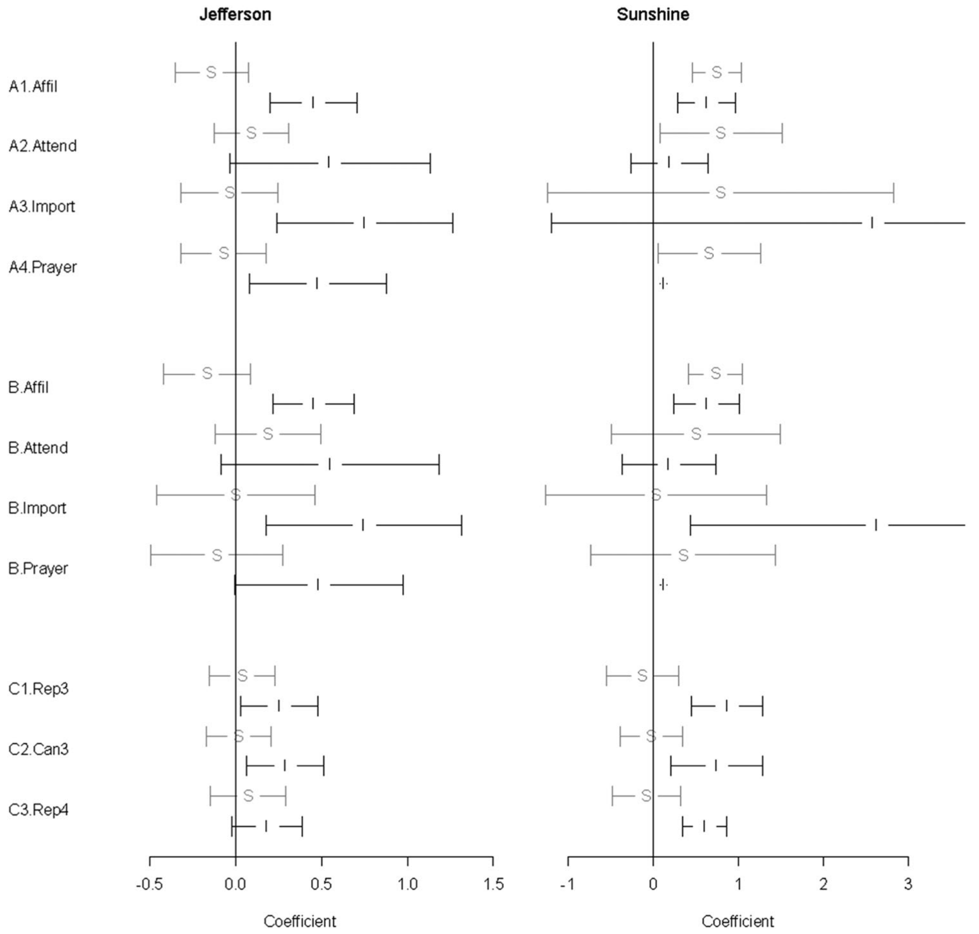
Network Dynamics

Estimating network selection and influence effects assumes the presence of network assortativity to be explained. As religious mosaics are categorical, we estimated the observed level of assortativity using the α segregation index (Moody 2001) for each school and wave.[16] The resulting odds ratios (see bottom row, Table 2) indicate that in each school, at both waves, ties

[15] Although we estimated LCA solutions separately for Wave 2, the substantive interpretations did not differ appreciably from those for Wave 1. As such, for clarity we discuss only Wave 1 LCA solutions. Comparable results for Wave 2 are available from the third author upon request.

[16] This index provides the properly conditioned form for asking how assortative ties are, given the general tendency for ties to form (Bojanowski and Corten 2014).

Figure 1
Religious selection & influence parameters from stochastic actor–based models



Note: The letters indicate SAB model estimates for friend selection (S) and peer influence (I) effects, respectively, for the specified religion measures, with error bars providing the 95% confidence intervals. Models in Panel A were estimated for each individual measure separately. The model in Panel B included all four religion indicators in a single estimation. The three models in Panel C were estimated separately for each latent class specification: 3-class replicate (Rep3), 3-class canonical (Can3), and 4-class replicate (Rep4).

are significantly more likely to form between two adolescents in the same LCA class compared to friendships between pairs with different LCA classes.

As described above, we ran a series of SAB models to test selection and influence on religion, while controlling for a range of potential confounding factors. Across models, estimates of our controls were as expected and consistent with prior studies using these data. For the sake of brevity, Figure 1 presents only the SAB model estimates for the parameters of selection and influence on the corresponding religion measures (results with full controls are provided in Supporting Information Tables A1 and A2). Of greatest interest for the present purpose is Model C1, panel C of Figure 1. These models correspond to our primary research question—how religious mosaics exert selection and/or influence effects—as modeled with the best fitting 3-class LCA solution using the replicate set of variables. Panels A and B present the preliminary models described above for each of the included religion indicators specifying their effects in separate models (A1-4) and a single composite model (B).

Model C1 shows that peer influence operates on replicate variable–derived religious profiles. For example, in Jefferson HS the influence estimate of .26 indicates that for each additional friend an adolescent has in a particular LCA class, the odds of choosing that class increase by 30 percent (exp[.26]), all else being equal. This effect is stronger in Sunshine HS, with a 139 percent increase (exp[.87]) in selecting a specified LCA class from each additional friend the adolescent has in that class. Thus, in both schools we see that adolescents are more likely to adopt an LCA class over time when they have more friends in that class, relative to other classes.

These same models also tested for whether adolescents select friends with the same religious class assignment as themselves. The results indicate that in neither school was selection based on common class membership significant. Thus, we have no evidence that adolescents choose friends with the same religious identity as themselves. Instead, observed assortativity on religious class can be attributed to interpersonal influence processes, or is accounted for by the other effects controlled in the model.

SAB models relying on the alternate LCA specifications show similar results. The canonical 3-class solution (Model C2) pattern is the same as Model C1 across both schools. The 4-class solution (Model C3) also shows influence but not selection on class membership; however, the effect of peer influence in Jefferson High School (two-tailed $p = .07$) did not reach the conventional level of significance. In combination, the results for the class profile models suggest that adolescents are increasingly likely to adopt the latent religious class memberships of their friends over time, but do not select friends based on those classes.

Discussion and Conclusions

Our aim was to determine whether religious mosaics provide a basis for peer influence and/or homophilous friend selection. To address this question, we first estimate LCA solutions using the "replicate" variables that most closely resemble the behavioral orientation employed by Pearce et al. (2013). This model identified three classes, which roughly correspond to adolescents with no, high, and moderate levels of religion. These results suggest it is worthwhile for survey researchers to continue exploring additional empirical and theoretically oriented strategies for incorporating these notions of religious mosaics into future research. Even in the face of limited religious measures, there may be added value to exploring the mosaic conceptualization of religion.

With these religious profiles in hand, we found evidence that religious mosaics are intertwined with adolescents' friendship processes. In particular, we found evidence for peer influence effects, but not selection, related to religious mosaics.[17] Over time, adolescents tended to become more like their friends on the ways their religious attributes clustered together. Thus, we found evidence of the expected pattern of peer influence on religious mosaics. The absence of selection effects here could suggest that religious selection genuinely does not operate among adolescents, works in other ways (e.g., only on individual variables; see panels A and B of Figure 1), or could reflect the imperfect measures (especially due to the skip patterns) available in Add Health. In the remainder of the paper, we discuss the implications of these findings for future studies of adolescent religion and peer networks.

For conceptualizing and measuring religion, our LCA results suggest that it is possible to incorporate the theoretical aims that correspond with the "lived religion" orientation into studies even where religion is not the focus and only limited information on religion is available. Although Pearce et al. (2013) demonstrate the robustness of their approach when using a portion of the

[17] Influence mechanisms have recently been shown to vary considerably as well. For example, Haas and Schaefer (2014) found influence processes to be stronger for smoking initiation than for smoking cessation. Moreover, both selection and influence effects can vary over time (de la Haye et al. 2013; Schaefer et al. 2010). While such differentiations are theoretically and empirically possible here, we leave that to future extensions of our work.

variables available in National Study of Youth and Religion (NSYR), our approach provides additional support that mosaics are broadly usable for conceptualizing and modeling adolescent religion. Perhaps future work can resolve some of the misalignment between our identified classes and those from the NSYR (e.g., how much these differences were simply driven by Add Health's unfortunate skip pattern). Additionally, it is important to consider whether mosaics change as populations age, and how the peer-based religious effects identified here (i.e., influence but not selection on mosaics) may shift across stages of the life course.

Although not our focus here, the empirical cases we drew on also suggest future research should investigate whether and how the modeled effects differ across contexts. We observed large differences in the distribution of classes between the two schools examined—the highly religious class was by far the largest in Sunshine HS, while the more moderately religious class was the majority in Jefferson HS. Despite this discrepancy, the composition of classes differed only modestly between the schools. Namely, the 4-class solution identified a group of religious "Adapters" in each school who attended services infrequently and who indicated religion was either fairly important (Sunshine High School) or less important (Jefferson High School). Perhaps most striking is that religious profiles showed consistent network patterns across schools, variables used, and number of classes identified—a consistent pattern of religious peer influence but not religion-based friend selection. There is accumulating evidence in religious (Ammerman 1997) and network (adams and Schaefer 2016) scholarship suggesting that an important avenue for future research is to more carefully consider how such contextual differences may alter what we know from studies of single cases, or models that assume similar patterns across entire populations.

One such possibility for network scholarship would be to consider whether influence and/or selection processes may differ across groups. For example, in highly religious schools (like Sunshine), the salience of religion for selection may be stronger for the less religious (who are the numeric minority), or vice versa in less religious schools. Such a result may explain the lack of selection effects observed here—if, in effect, a strong religious selection process among the highly religious class and a true absence of effect among the irreligious canceled each other out. Heterogenous effects, either by group or context, are not frequently considered in networks research. For one exception, Goodreau et al. (2009) found that racial friendship homophily was stronger for those groups that were numeric minorities within their schools. Unfortunately, estimating such contextual differences likely requires many more schools than are currently available in Add Health, but would be a fruitful avenue for future research.

In summary, religion is a multidimensional construct that cannot simply be reduced to individual and/or variable level assessment. People combine various aspects of religion into unique constellations, which are shaped by others in their contexts. We demonstrated how to employ recent methodological advances in the modeling of categorical variables as two-mode networks (Snijders et al. 2013) to investigate how peers are involved in developing these norms (e.g., potentially through influence and selection). We found suggestive empirical evidence for how these play out in two different school contexts. We encourage future research to further elaborate whether and how adolescents' religious mosaics shape and are shaped by their friendship networks.

References

adams, jimi. 2019. *Gathering social network data*. Newcastle: SAGE.

adams, jimi and David R. Schaefer. 2016. How initial prevalence moderates network-based smoking change: Estimating contextual effects with stochastic actor based models. *Journal of Health and Social Behavior* 57(1): 22–36.

Ammerman, Nancy T. 1997. *Congregation and community*. New Brunswick, NJ: Rutgers University Press.

———. 2007. *Everyday religion: Observing modern religious lives*. New York, NY: Oxford University Press.

Bearman, Peter S., Jo Jones, and J. Richard Udry. 1997. The national longitudinal study of adolescent health: Research design. Carolina Population Center, University of North Carolina-Chapel Hill, and Inter-university Consortium for Political and Social Research.

Berger, Christian and Jan Kornelis Dijkstra. 2013. Competition, envy, or snobbism? How popularity and friendships shape antipathy networks of adolescents. *Journal of Research on Adolescence* 23(3):586–95.

Blau, Peter M. 1977. *Inequality and heterogeneity: A primitive theory of social structure*. New York, NY: Free Press.

Bojanowski, Michał and Rense Corten. 2014. Measuring segregation in social networks. *Social Networks* 39:14–32.

Bray, Bethany C., T. Lanza Stephanie, and Tan Xianming. 2015. Eliminating bias in classify-analyze approaches for latent class analysis. *Structural Equation Modeling* 22(1):1–11.

Brechwald, Whitney A. and Mitchell J. Prinstein. 2011. Beyond homophily: A decade of advances in understanding peer influence processes. *Journal of Research on Adolescence* 21:166–79.

Brown, B. Bradford, Heather Von Bank, and Laurence Steinberg. 2008. Smoke in the looking glass: Effects of discordance between self- and peer rated crowd affiliation on adolescent anxiety, depression and self-feelings. *Journal of Youth and Adolescence* 37:1163–77.

Cheadle, Jacob E., and Philip Schwadel. 2012. The 'friendship dynamics of religion,' or the 'religious dynamics of friendship'? A social network analysis of adolescents who attend small schools. *Social Science Research* 41:1198–212.

Cook, J. Benjamin, Philip Schwadel, and Jacob E. Cheadle. 2017. The origins of religious homophily in a medium and large school. *Review of Religious Research* 59:65–80.

Cornwall, Marie, Stan L. Albrecht, Perry H. Cunningham, and Brian L. Pitcher. 1986. The dimensions of religiosity: A conceptual model and an empirical test. *Review of Religious Research* 27(3):226–44.

de la Haye, Kayla, Harold D. Green, David R. Kennedy, Michael Pollard, and Joan S. Tucker. 2013. Selection and influence mechanisms associated with marijuana initiation and use in adolescent friendship networks. *Journal of Research on Adolescence* 23:474–86.

de la Haye, Kayla, Garry Robins, Philip Mohr, and Carlene Wilson. 2011. How physical activity shapes and is shaped by adolescent friendships. *Social Science and Medicine* 73(5):719–28.

Deci, Edward L. and Richard M. Ryan. 2011. Levels of analysis, regnant causes of behavior and well-being: The role of psychological needs. *Psychological Inquiry* 22:17–22.

Dijkstra, Jan Kornelis, Scott D. Gest, Siegwart Lindenberg, Rene Veenstra, and Antonius H. N. Cillessen. 2012. Testing three explanations of the emergence of weapon carrying in peer context: The roles of aggression, victimization, and the social network. *Journal of Adolescent Health* 50(4):371–76.

Ellison, Christopher G., and Jeffrey S. Levin. 1998. The religion-health connection: Evidence, theory, and future directions. *Health Education & Behavior* 25(6):700–20.

Feld, Scott L. 1981. The focused organization of social ties. *American Journal of Sociology* 86:1015–35.

George, Linda K., Christopher G. Ellison, and David B. Larson. 2002. Explaining the relationships between religious involvement and health. *Psychological Inquiry* 13(3):190–200.

Goodreau, Steven M., James A. Kitts, and Martina Morris. 2009. Birds of a feather or friend of a friend? Using exponential random graph models to investigate adolescent social networks. *Demography* 46(1):103–25.

Green, Harold D., Mariana Horta, Kayla de la Haye, Joan S. Tucker, David R. Kennedy, and Michael Pollard. 2013. Peer influence and selection processes in adolescent smoking behavior: A comparative study. *Nicotine & Tobacco Research* 15(2):534–41.

Haas, Steven A. and David R. Schaefer. 2014. With a little help from my friends: Asymmetrical social influence on adolescent smoking initiation and cessation. *Journal of Health and Social Behavior* 55(2):126–43.

Hadaway, C. Kirk, Penny L. Marler, and Mark Chaves. 1993. What the polls don't show - a closer look at United-States Church attendance. *American Sociological Review* 58(6):741–52.

———. 1998. Overreporting Church attendance in America: Evidence that demands the same verdict. *American Sociological Review* 63(1):122–30.

Jung, Tony and Kandauda A. S. Wickrama. 2008. An introduction to latent class growth analysis and growth mixture modeling. *Social and Personality Psychology Compass* 2(1):302–17.

Kandel, Denise B. 1978. Homophily, selection, and socialization in adolescent friendships. *American Journal of Sociology* 84:427–36.

Kirke, Deirdre M. 2004. Chain reactions in adolescents' cigarette, alcohol and drug use: Similarity through peer influence or the patterning of ties in peer networks. *Social Networks* 26:3–28.

Kornienko, Olga, Carlos E. Santos, and Kim Updegraff. 2014. Friendship networks and ethnic identity development: Contributions from social network analysis. In *Studying ethnic identity: Methodological advances and considerations for future research*, edited by C. E. Santos and A. Umaña-Taylor, pp. 177–202. Washington, DC: American Psychological Association.

Kornienko, Olga, Carlos E. Santos, Carol Lynn Martin, and Kristen L. Granger. 2016. Peer influence on gender identity development in adolescence. *Developmental Psychology* 52: 1578–92.

Kossinets, Gueorgi and Duncan J. Watts. 2009. Origins of homophily in an evolving social network. *American Journal of Sociology* 115(2):405–50.

Lehrer, Evelyn L. 1999. Religion as a determinant of educational attainment: An economic perspective. *Social Science Research* 28:358–79.

Lewis, Kevin and Jason Kaufman. 2018. The conversion of cultural tastes into social network ties. *American Journal of Sociology* 123(6):1684–1742.

Linzer, Drew and Jeffrey Lewis. 2014. poLCA: An R package for polytomous variable latent class analysis. *Journal of Statistical Software* 42(10):1–29.

Marsden, Peter V. 1988. Homogeneity in confiding relations. *Social Networks* 10:57–76.

McCutcheon, Allen L. 1987. *Latent class analysis*. Newcastle: SAGE.

McGuire, Meredith. 2008. *Lived religion: Faith and practice in everyday life*. New York, NY: Oxford University Press.

McPherson, J. Miller and Lynn Smith-Lovin. 1987. Homophily in voluntary organizations: Status distance and the composition of face-to-face groups. *American Sociological Review* 52: 370–79.

McPherson, Miller, Lynn Smith-Lovin, and James M. Cook. 2001. Birds of a feather: Homophily in social networks. *Annual Review of Sociology* 27:415–44.

Mercken, L, T. A. B., Snijders, C., Steglich, E., Vartiainen, and H. de Vries. 2010. Dynamics of adolescent friendship networks and smoking behavior. *Social Networks* 32:72–81.

Moody, James. 2001. Race, school integration, and friendship segregation in America. *American Journal of Sociology* 107(3):679–716.

Nagin, Daniel S. 2005. *Group-based modeling of development over the life course*. Cambridge, MA: Harvard University Press.

Paxton, Pamela, and James Moody. 2002. Structure and sentiment: Explaining emotional attachment to group. *Social Psychology Quarterly* 66:34–47.

Pearce, Lisa D., and Melinda Lundquist Denton. 2011. *A faith of their own: Stability and change in the religiosity of America's adolescents*. Oxford: Oxford University Press.

Pearce, Lisa D., Jessica Halliday Hardie, and E. Michael Foster. 2013. A person-centered examination of adolescent religiosity using latent class analysis. *Journal for the Scientific Study of Religion* 52(1):57–79.

Pearce, Lisa D., and Dana L. Haynie. 2004. Intergenerational religious dynamics and adolescent delinquency. *Social Forces* 82(4):1553–72.

Regnerus, Mark D. 2000. Shaping schooling success: Religious socialization and educational outcomes in metropolitan public schools. *Journal for the Scientific Study of Religion* 39(3):363–70.

Regnerus, Mark D., and Jeremy E. Uecker. 2006. Finding faith, losing faith: The prevalence and context of religious transformations during adolescence. *Review of Religious Research* 47(3):217–37.

Ridgeway, Cecilia L., and Lynn Smith-Lovin. 1999. The gender system and interaction. *Annual Review of Sociology* 25:191–216.

Ripley, Ruth M., Tom A.B. Snijders, Zsófia Boda, András Voros, and Paulina Preciado. 2013. *Manual for RSIENA*.

Rivas-Drake, Deborah, Adriana Umaña-Taylor, David R. Schaefer, and Michael Medina. 2017. Ethnic-racial identity and friendships in early adolescence. *Child Development* 88: 710–24.

Schaefer, David R., Olga Kornienko, and Andrew M. Fox. 2011. Misery does not love company: Network selection mechanisms and depression homophily. *American Sociological Review* 75(5):764–85.

Schaefer, David R., Sandra D. Simpkins, and Andrea E. Vest. 2018. Can extracurricular activities reduce adolescent race/ethnic friendship segregation? In *Social networks and the life course*, edited by D. Alwin, D. Felmlee, and D. Kreager, pp. 315–39. New York, NY: Springer.

Schaefer, David R., Sandra R. Simpkins, Andrea E. Vest, and Chara D. Price. 2011. The contribution of extracurricular activities to adolescent friendships: New insights through social network analysis. *Developmental Psychology* 47(4):1141–52.

Sepulvado, Brandon, David Hachen, Michael Penta, and Omar Lizardo. 2015. Social affiliation from religious disaffiliation: Evidence of selective mixing among youth with no religious preference during the transition to college. *Journal for the Scientific Study of Religion* 54(4):833–41.

Smith, Christian, and Melinda Lundquist Denton. 2005. *Soul searching: The religious and spiritual lives of American teenagers*. New York, NY: Oxford University Press.

Smith, Christian, and Patricia Snell. 2009. *Souls in transition: The religious lives of emerging adults in America*. New York, NY: Oxford University Press.

Snijders, Tom A. B. 2011. Statistical models for social networks. *Annual Review of Sociology* 37:129–51.

Snijders, Tom A. B., Alessandro Lomi, and Vanina Jasmine Torló. 2013. A model for the multiplex dynamics of two-mode and one-mode networks, with an application to employment preference, friendship, and advice. *Social Networks* 35(2):265–76.

Snijders, Tom A. B., Gerhard van de Bunt, and Christian E. G. Steglich. 2010. Introduction to stochastic actor-based models for network dynamics. *Social Networks* 32:44–60.

Steensland, B., J. Z. Park, M. D. Regnerus, L. D. Robinson, W. B. Wilcox, and R. D. Woodberry. 2000. The measure of American religion: Toward improving the state of the art. *Social Forces* 79(1):291–318.

Steglich, Christian, Tom A. B. Snijders, and Michael Pearson. 2010. Dynamic networks and behavior: Separating selection from influence. *Sociological Methodology* 40(1):329–93.

Strang, David and Sarah A. Soule. 1998. Diffusion in organizations and social movements: From hybrid corn to poison pills. *Annual Review of Sociology* 24: 265–90.

Trinitapoli, Jenny, and Stephen Vaisey. 2009. The transformative role of religious experience: The case of short-term missions. *Social Forces* 88(1):121–46.

Trinitapoli, Jenny, and Alexander A. Weinreb. 2012. *Religion and AIDS in Africa*. Oxford: Oxford University Press.

Uecker, Jeremy, Mark D. Regnerus, and Margaret L. Vaaler. 2007. Losing my religion: The social sources of religious decline in early adulthood. *Social Forces* 85(4):1667–92.

Ueno, Koji, Eric R. Wright, Mathew D. Gayman, and Janice M. McCabe. 2012. Segregation in gay, lesbian and bisexual youth's personal networks: Testing structural constraint, choice homophily and compartmentalization hypotheses. *Social Forces* 90(3):971–91.

Vaisey, Stephen and Omar Lizardo. 2010. Can cultural worldviews influence network composition? *Social Forces* 4(1):1595–618.

van Workum, Nicole, Ron H. J. Scholte, Antonius H. N. Cillessen, Gerine Lodder, and Matteo Giletta. 2013. Selection, deselection, and socialization processes of happiness in adolescent friendship networks. *Journal of Research on Adolescence* 23: 563–73.

Van Zalk, Maarten H. W., Margaret Kerr, Susan J. T. Branjie, Hakan Stattin, and Wim H. J. Meeus. 2010. It takes three: Selection, influence, and de-selection processes of depression in adolescent friendship networks. *Developmental Psychology* 46(4):927–38.

Veenstra, Rene, Jan Kornelis Dijkstra, Christian E. G. Steglich, and Maarten H. W. Van Zalk. 2013. Network-behavior dynamics. *Journal of Research on Adolescents* 23(3):399–412.

Vermut, Jeroen K., and Jay Magidson. 2002. Latent cluster analysis. In *Applied latent class analysis*, edited by J. A. Hagenaars and A. L. McCutcheon, pp. 89–106. New York: Cambridge.

Wimmer, Andreas, and Kevin Lewis. 2010. Beyond and below racial homophily: ERG models of a friendship network documented on facebook. *American Journal of Sociology* 116(2):583–642.

Supporting Information

Additional supporting information may be found online in the Supporting Information section at the end of the article.

Table A1. Full SABM results for jefferson HS
Table A2. Full SABM results for sunshine HS