Supplemental material for "Political Speech in Religious Sermons"

A Standardizing the community-generated labels and finding political speech

Given the free-form nature of the labels and the overall size of the sermons corpus, we observe an extensive list of community-generated tags (N = 19,525). To standardize the labels for analysis and identify the labels associated with politics, we employed a three step procedure. First, for an initial examination of the political tags in the overall label set, we turn to crowd-sourcing via the popular online service Crowdflower (Benoit et al. 2016).[1] Specifically, after providing a brief set of instructions and training session, we asked the workers to rate each community-generated label on a seven-point scale from "Not at all political" to "Clearly political" (see the appendix for a detailed description of the coding task). Five workers rated each label, giving us both an average political score and a reliability measure for each label. Perhaps unsurprisingly, the vast majority of labels are not political: restricting attention to the set of labels scoring an average of five or higher on the political scale reduced the number of relevant tags from over 19,000 to just over 500.

Second, after reducing the set of possible political labels to a manageable number, we more thoroughly assess whether a particular label was political by reading the content of a small sample of sermons (up to 5 sermons; see Quinn et al. 2010 for a similar approach). This process allows us to disambiguate seemingly political terms and place labels in their appropriate religious context. For instance, while many would consider the term ”Left” to be political, the use of the term in sermons related instead to the rapture and being ”left behind” in salvation. Completing this review process and collapsing synonymous labels (e.g., ”Election 2016” and ”election 2016” or ”911” and ”9/11”) left 231 politically related tags or approximately 1% of the total tags (see the online appendix for a complete list of political tags).

Third, even a cursory glance at the remaining 231 labels suggests considerable overlap and thus we further aggregated the political tags into 21 substantively meaningful categories. Specifically, we developed a coding rubric based on the primary "political" categories identified in previous large-scale national surveys of clergy (Djupe and Gilbert (2003)) and then added additional categories as necessary.[2] Table 1 provides a full list of the user-generated tags associated with each aggregate category. The labels were then coded into aggregate categories independently by the coauthors using the developed rubric (which is available below), resulting in a reliability score (Cronbach's α) of 0.92). Differences were reconciled via committee. Finally, a research assistant, blind to the hypotheses, replicated this aggregated coding scheme, resulting in a reliability score of 0.89.

Table 1: Full list of politically-relevant user-generated tags by aggregated label

[1] Crowdflower is a popular online platform where individuals complete tasks for compensation. Crowdflower workers differ from MTurk workers, however, because Crowdflower provides a more robust layer of screening through the use of 'gold standard' questions (see Benoit et al. 2016). Details on this process and our gold standard questions are available in the appendix.

[2] For example, the existing research that uses survey and observational data has a very limited discussion of foreign affairs or terrorism, but we find that pastors do engage in discussions of these topics. Other topics emerge as popular give political events over the last several years that have occurred since this literature, such as health care.

Aggregated label	User-generated tags
Abortion	“Abortion” “Birth Control” “Hobby Lobby” “Human Life” “Infanticide”
	”Planned Parenthood” “Privacy” “Pro Life” “Pro-life” “Women Leadership”
	“Womenx92s Rights” “Womenxe2x80x99s Rights”
American Values	“America’s Decline” “American Dream” “American Heritage” “American Values”
	“Change In America” “Cultural Change” “Judgment Of America” “Morals Police”
	“National Revival” “The American Way”
Civil Rights	“Activism” “African American” “American Indian” “Anti-semitism”
	“Baltimore Riots” “Bias” “Civil Rights” “Civil”
	“Discrimination” “Emancipation” “Equal Justice” “Equality”
	“General Grant” “Gettysburg” “Ghandi” “Injustice”
	“Injustices” “Justice For All” “Justice” “Martin Luther King Jr”
	“Martin Luther King” “Movement” “Native American” “Nelson Mandela”
	“Predjudice” “Prejudice” “Racial Barriers” “Racism”
	“Social Action” “Social Justice” “Underground Railroad”
Crime	“Breaking The Law” “Court Case” “Court Room” “Criminal”
	“Drugs” “Guns” “Lawless” “Police” “Policeman”
	“Prison” “Sentencing” “Violence” “Weapon”
Economy	“Bail Out” “Bills” “Business And Marketplace” “Capitalism”
	“Commercialism” “Consumerism” “Currency” “Debt Release” “Deficit”
	“Economia” “Economics” “Economy Of Exclusion” “Economy”
	“Employment” “Financially” “Investments” “Just Wages”
	“Labor Day” “Labor” “Monetary” “Money Mangement”
	“National Debt” “Operating Budget” “Recession” “Spend Less Save More”
	“Stuck On The Bottom” “Tax Collectors” “Trabajo” “Treasury”
	“Wages” “Wealth” “Workplace Unemployment” “World Trade”
Education	“College” “Education” “Failure Of Public Ed”
Elections	“2016 Election” “Buying Votes” “Campaign” “Civic”
	“Conservative” “Democrat” “Elect” “Election & Free Will”
	“Election 2016” “Election” “Elections” “Partisanship”
	“Protests” “Rally” “Republican Party” “Republican”
	“Republican” “Vote” “Voting”
Environment	“Conservation” “Ecosystem” “Environment” “Environmentalism”
	“Global Warming” “Michael D. Lemonick” “Storms And Jesus”
Evolution	“Evolution”
Founding	“Amendment” “Bill Of Rights” “Constitution” “Declaration Of Independence”
	“Early American Hist” “First Amendment” “Forefathers” “Founding Fathers”
	“Independence Day” “John Adams” “King George” “Liberty Bell”
	“Mayflower Compact” “Our Heritage” “Revolutionary War”
Govt General	“Bureaucracy” “Bush” “Capital Building” “Clinton”
	“Congress” “Country” “God And Government” “God Bless America”
	“Government” “Governmental Control” “Governmental Leaders” “Governor”
	“Governor” “House Of Representat” “House Of Representatives” “Human Government”
	“Inauguration” “Kennedy” “Legislation” “Lyndon Johnson” “Nixon”

	“Obama” “Parliament” “Political” “Politician” “Politics” “Politics” “Pray For Government” “President” “Presidential” “Presidents Day” “Regulations” “Representation” “Representative” “Secret Service” “Senate” “Senator” “State” “Statute” “Washington D.c.” “Washington State” “Washington” “White House”
Homosexuality	“Definition Marriage” “Gay Lifestyle” “Gay” “Homosexual” “Homosexuality” “Same-sex Marriage” “Sexual Immorality”
International	“Bulgaria” “Chilean” “China” “Diplomat” “European Union” “Foreign” “Korea” “Nations” “Russia” “Sri Lanka” “Syria” “Treaties” “United Nations” “Winston Churchill” “World Events” “World Needs” “World Peace” “World Religions” “World”
Law	“Cases” “Court” “Law Suits” “Legal System” “Legal” “Litigation” “Prosecutor” “Supreme Court”
Liberty	“Church And State” “Church Persecution” “Control Speech” “Duty To Government” “Free” “Freedom From The Law” “Freedom Of Speech” “Freedom Vs Licence” “Freedom” “God & Government” “Hobbes” “Independence” “Liberty” “Magna Carta” “Political Freedom” “Public Faith” “Religion & Politics” “Religious Freedom” “Rights” “Rights–perversion” “Self Government”
Military/patriotism	“Air Force” “American Flag” “Armed Forces” “Army” “Flag” “July Fourth” “Lady Liberty” “Marines” “Memorial Day” “Military Appreciatio” “Military” “Monument” “Nationalism” “Navy” “Patriotic” “Patriotism” “Remembrance Day” “Soldier” “Star Spangled” “Troops” “Veteran” “Veterans Day” “Veterans”
Stem Cell	“Bioethics” “Stem-cell”
Terrorism	“9-11 Attacks” “911” “Bin Laden” “Isil” “Islamic Extremism” “Jihad” “Terrorism” “Terrorist”
Govt Type	“Communism” “Communist” “Democracy” “Revolution” “Revolutionary” “Socialism” “Tyranny” “Tyrants”
War	“Afghanistan” “Art Of War” “Assassination” “Auschwitz” “Berlin Wall” “Blitzkrieg” “Civil War” “Combat” “Defense” “Douglas Macarthur” “Germany” “Gulf War” “Hitler” “Invasion” “Iran” “Iraq” “Just War Theory” “Machine Guns” “Missile” “Nazi Germany” “Nazi” “Nuclear War” “Nuclear Winter” “Nuclear” “Peace In The World” “Peace On Earth” “Peacekeeping” “Syrian Wars” “War Or Peace” “War” “Warfare” “World War 2”
Welfare	“Acts Of Service” “Care For Elderly” “Health Care” “Homeless” “Marginalise” “Poverty” “Service To Humanity” “Welfare” “World Vision”

B Learning political labels via a supervised LDA model

This section provides a more technical discussion of the labelled (or "flat LDA" employed in the main text. Here, we draw heavily on the discussion of supervised generative models in Rubin et al. (2012). Consistent with the standard, unsupervised LDA (Blei, Ng, and Jordan 2003; Griffiths and Steyvers 2004), the labelled LDA is "a simple hierarchical Bayesian model based on the following assumptions: 1) each word in a text is exchangeable, each text in a corpus is a combination of a fixed number of topics (T), and each topic is represented as a distribution of words (w) over a fixed vocabulary (W). The generative structure that produces each document in a corpus is represented as random mixtures of latent topics and their associated distributions of words" (Boussalis, Coan, and Holman 2018, p. 92). Moreover, the actual generative process is very similar to the standard LDA, with the exception that the set of available topics for a given document is constrained to the *observed labels* associated with that document (t^d) and thus there is an assumed one-to-one association between "topics" in the traditional model and "labels" in the supervised version. Specifically, the generative model is as follows (Rubin et al. 2012):

1. For each topic (label) $t \in \{1 \ldots T\}$, sample from a topic distribution over words:

$$\phi_t \sim Dirichlet(\beta)$$

2. For each document $d \in \{1 \ldots D\}$,

   Sample a topic (label) distribution from the set of observed labels (t^d) for d:

$$\theta_d \sim Dirichlet(\alpha)$$

   For each word $i \in \{1 \ldots N_d^W\}$ in document d:

   Sample a topic $z_i^d \sim Multinomial(\theta_d)$.

   Sample a word $w_i^d \sim Multinomial(\phi_t)$ from the topic $t = z_i^d$

With the generative, hierarchical process in hand, estimation is carried out using a slightly modified version of the standard collapsed Gibbs sampler (see Griffiths and Steyvers 2004), which incorporates the constraint that topics must be chosen from the observed label set (t^d) for each document. For "collapsed" Gibbs sampling, one integrates out the primary parameters of interest (ϕ and θ_d) and instead preforms inference on the latent indicator variable for whether a particular word in a given document is assigned to a particular topic, z_i^d. Specifically, sampling is performed using the following update equation:

$$P(z_i^d = t | w_i^d, w_{-i}, t^d, \alpha, z_{-i}, \beta) \propto \frac{N_{wt,-i}^{WT} + \beta}{\sum_{w'=1}^{W}(N_{w't,-i}^{WT} + \beta)} * (N_{td,-i}^{TD} + \alpha) \tag{1}$$

where the parameters are as follows:

z_i^d: the latent topic assignment for word i in document d

w_i^d: word i in document d

w_{-i}: all words other than w_i^d

α: prior distribution over words

z_{-i}: all latent assignments other than z_i^d

β: prior distribution over documents

$N^{WT}_{wt,-i}$: the total number of times word w has been assigned to topic T, but not including the current word under consideration.

$N^{TD}_{td,-i}$: the total number of times topic t is assigned in document d, but not including the current word under consideration.

We use Equation 1 to train our model to classify sermon content, relying on observed, community generated labels for each sermon. Consistent with the recommendations in Rubin et al. (2012), we set $\beta = 0.01$ and $\alpha = 50$. However, alternative assumptions for the hyperparameters made little difference for the substantive findings presented in the text.

As discussed in the main text, while sermons with observed political labels very often are about politics, the converse is not necessarily true. An extensive reading of the underlying sermon content suggests that often politically-relevant sermons are not labelled as such and thus using the observed labels alone is likely to underestimate the proportion of political content. In order to estimate the "missing" political labels, we treat all of the sermon labels (observed and unobserved) as unobserved and use the trained model to infer missing labels. Specifically, we use the following update equation to infer new labels (Rubin et al. 2012):

$$P(z_i^d = t | w_i^d = w, w_{-i}^d, \alpha, z_{-i}^d, \hat{\phi}_{w,c}) \propto \hat{\phi}_{w,c} * (N^{TD}_{td,-i} + \alpha) \tag{2}$$

As such, we update our inferences based on the fixed estimate $\hat{\phi}_{w,c}$ recovered during training. We wrote software in **R** and C++ to carry out the estimation routine, which is available at [website removed for peer-review].

C Topic prevalence as the proportion of politically-relevant words

Figure 1 displays the proportion of total words in the corpus that are assigned to each politically-relevant topic. Specifically, we show the proportion of total words in the corpus that are associated with each of the 21 political topics. At the top of the list, we find that 2.1% of the 118 million words in the corpus are assigned to the *Economy* theme by the model. Using this metric, we can see that topics such as *Homosexuality*, *War*, *Welfare*, *Civil Rights*, and *Abortion* also receive relatively high levels of attention by pastors; whereas, themes such as *Stem Cell* and *Terrorism* have been discussed less. Overall, these results conform with the other prevalence metrics reported in the text.

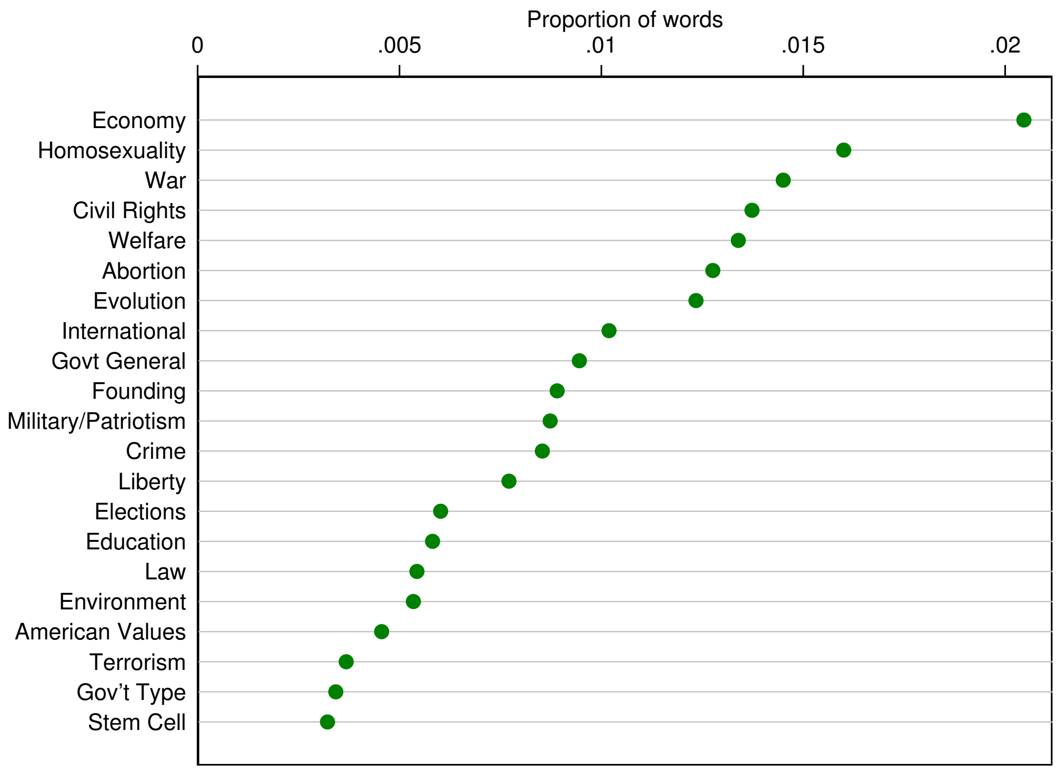


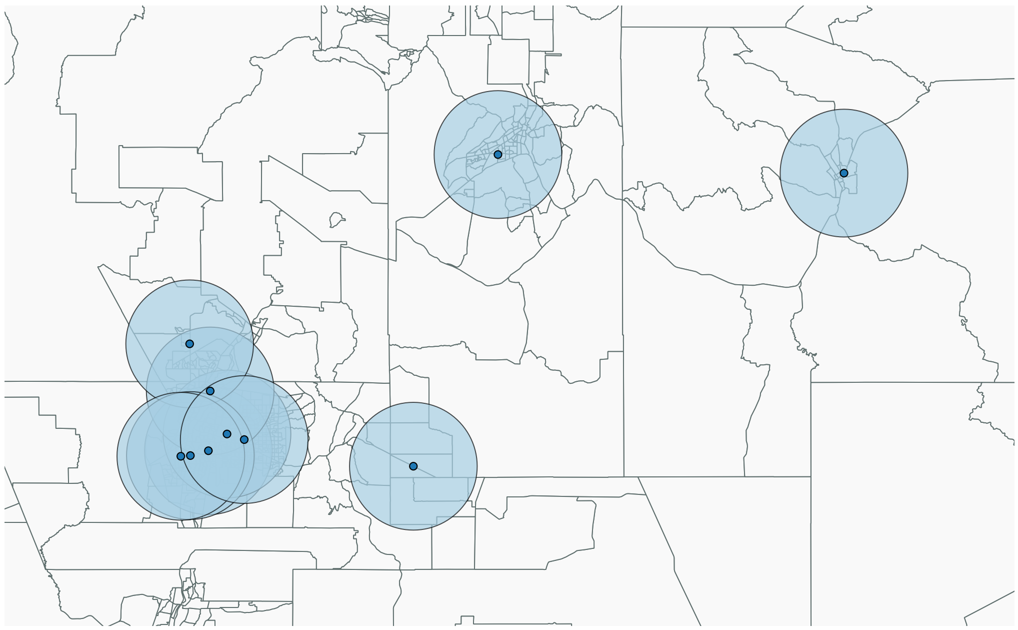
Figure 1: Proportion of total words in the corpus by topic

D Estimating the church "neighborhood" and "community"

After geocoding each church's address, we used Geographic Information Systems (GIS) to construct two variables: church "neighborhood" and "community." Based on transportation statistics from the U.S. Department of Transportation 2009 Household Travel Survey (Santos et al. 2011, p.13) and literature on "church growth" (Warren 1995), we estimate that the majority of congregants will travel no more than 10 miles to attend church and thus set this distance as the geographic boundary of a given church's "neighborhood." Specifically, we define each church's neighborhood as the set of block groups (for Census data) or precincts (for election data) and average over these areas to arrive at our independent variables of interest (see appendix Figure 2a).

Next, since churches with overlapping "neighborhoods" are, by definition, statistically dependent, we need a way to incorporate this dependence when examining the correlates of political speech. To achieve this objective, we construct a variable to capture each church's "community" and cluster on this variable when estimating the relationship between political, economic, and demographic factors and sermon content in the results section of the text. We define a church "community" as the union of overlapping neighborhoods. Figure 2 illustrates this process. Specifically, after defining the church community as described above (blue area in appendix Figure 2a), we form the geographic union of intersecting 10 mile buffers (i.e., the orange area in appendix Figure 2b). Overall, while our estimated "neighborhoods" and their implied "communities" offer a somewhat coarse estimate of the potential area served by a particular church, this procedure more closely aligns with available data on the distance of a typical commute to church.

(a) Church "neighborhoods" (based on 10 mile buffer)



(b) Church "communities" (union of neighborhoods)

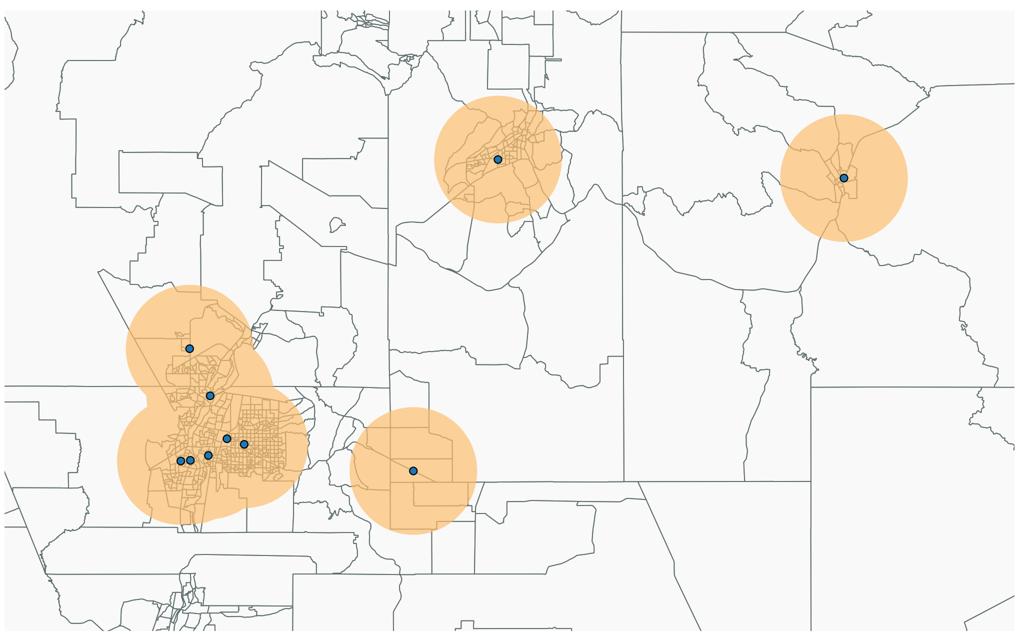


Figure 2: *Constructing neighborhoods and communities.*

E Full list of estimated topics

Table 2: This table displays the full list of estimated topics produced by the topic model. Each topic's descriptive label and top 10 most probable keywords are listed.

Topic label	Top 10 keywords
Abortion	abort, babi, human, womb, creat, mother, child, children, kill, unborn
American Values	nation, christian, america, american, law, evil, found, countri, salt, citi
Antichrist	beast, antichrist, daniel, shall, power, king, end, earth, horn, revel
Belief	john, son, father, discipl, belief, doubt, shall, heal, save, unbelief
Bible	bibl, spirit, shall, book, son, holi, scriptur, truth, law, paul
Blessing	bless, shall, father, son, name, receiv, prais, promis, spirit, peac
Christ	son, spirit, father, john, christian, name, power, holi, year, christma
Christian Elections	elect, paul, chosen, predestin, israel, salvat, grace, choos, save, merci
Christian Liberty	law, free, paul, freedom, spirit, christian, set, eat, flesh, condemn
Church	spirit, paul, christian, holi, togeth, bodi, new, anoth, worship, teach
Civil Rights	justic, jew, black, peter, nation, king, law, differ, poor, year
Crime	prison, joseph, paul, peter, fear, hate, drink, someon, suffer, happen
Death	death, die, bodi, heaven, dead, etern, shall, son, hope, year
Devil Hell	satan, hell, devil, angel, heaven, power, evil, enemi, spirit, fire
Disciple	follow, discipl, christian, peter, john, spirit, paul, father, son, other
Economy	money, rich, wealth, labor, poor, job, year, well, eat, much
Education	educ, school, christian, children, year, student, hell, bibl, public, learn
Elections	vote, nation, king, author, elect, leader, govern, candid, pray, name
Endurance	paul, christian, spirit, suffer, power, help, back, stand, son, year
Environment	earth, environ, creation, distort, global, warm, hostil, destroy, noah, human
Eternal	etern, son, father, john, heaven, death, shall, die, save, gift
Evangelism	christian, spirit, paul, gospel, save, power, john, holi, share, discipl
Evolution	evolut, earth, creat, creation, year, bibl, begin, heaven, light, theori
Faith	son, spirit, paul, power, christian, promis, father, trust, hope, year
Forgiveness	forgiv, father, son, grace, other, back, brother, someon, forgiven, merci
Founding	nation, america, freedom, christian, free, bless, countri, law, men, pray
God	father, son, power, spirit, name, heaven, holi, shall, kingdom, hand
Gospel	gospel, paul, john, preach, son, peter, power, spirit, name, save
Govt General	govern, author, christian, polit, nation, king, law, tax, state, establish
Grace	grace, law, paul, save, spirit, son, gift, christian, receiv, salvat
Heaven	heaven, new, earth, bodi, etern, die, prepar, death, citi, home
Holiness	spirit, holi, power, thank, christian, father, fill, paul, receiv, speak
Homosexuality	homosexu, sexual, marriag, men, sex, gay, woman, christian, natur, bibl
Hope	hope, promis, power, peac, spirit, new, shall, year, son, death
International	christian, muslim, islam, religion, son, mormon, bibl, father, teach, name
Joy	joy, paul, rejoic, thank, suffer, happi, christian, spirit, bless, alway
Judgement	judgment, judg, shall, earth, heaven, nation, israel, book, angel, king
Law	court, shall, joshua, wit, stand, law, suprem, upon, serv, gate
Liberty	freedom, free, nation, christian, law, liberti, govern, america, set, truth
Love	anoth, other, spirit, christian, john, father, kind, son, command, paul
Military/Patriotism	soldier, nation, memori, rememb, war, freedom, fight, men, countri, christian
Obedience	obedi, obey, command, jonah, israel, son, mose, follow, king, land
Other	father, spirit, son, year, christian, power, children, paul, holi, name
Peace	peac, paul, mind, spirit, patienc, wait, find, worri, understand, christian
Prayer	prayer, pray, father, answer, power, spirit, name, heaven, holi, help
Repentance	repent, turn, john, chang, son, father, spirit, forgiv, back, away

Resurrection	resurrect, death, dead, tomb, die, discipl, bodi, power, rais, cross
Salvation	save, salvat, son, spirit, john, etern, death, father, shall, heaven
Scandal	lie, truth, fals, christian, speak, father, tongu, satan, corrupt, jacob
Serventhood	serv, servant, paul, servic, gift, other, christian, ministri, bodi, spirit
Sin	law, death, spirit, david, evil, die, paul, away, son, shall
Stem Cell	human, cell, research, clone, embryo, genet, diseas, stem, scienc, moral
Terrorism	muslim, islam, christian, nation, year, hate, america, muhammad, isi, allah
Trust	trust, king, david, saul, esther, fear, hand, mordecai, went, son
Truth	truth, bibl, spirit, john, christian, teach, father, scriptur, true, paul
Type Govt	govern, christian, nation, radic, poor, state, america, gener, communist, share
Unity	uniti, paul, anoth, togeth, spirit, bodi, christian, other, part, differ
War	war, enemi, battl, power, fight, stand, devil, satan, spiritu, peac
Welfare	poor, poverti, rich, help, money, bless, shall, cloth, food, needi
Worship	worship, prais, holi, spirit, sing, offer, psalm, name, david, song

F Sample representativeness

Table 3: U.S. Census benchmarking

	2000		2010/2014	
	Overall counties	*Our sample*	*Overall counties*	*Our sample*
Median Population	87,420	147,250	96,024	167,641
Median income	$38,764	$40,192	$49,566	$50,690
Poverty rate for families	10.00	9.66	12.31	12.36
Poverty rate for individuals	13.28	12.88	16.59	16.58
Median age			38.60	37.81
White %	80.13	78.59	77.68	75.73
Black %	11.16	12.27	11.65	12.90
Asian %	1.84	2.19	2.49	2.96
Hispanic %	2.56	2.57	11.37	12.14
Owner Occupancy rate	70.51	69.30	68.86	67.58
% with HS diploma or higher	78.70	79.17	85.49	85.68
% with BA or higher	36.18	35.66	23.86	25.54

Table 4: U.S. Religious Census benchmarking

	2000		2010/2014	
	Overall counties	*Our sample*	*Overall counties*	*Our sample*
Total rate of adherence	509.86	499.63	503.96	497.79
Mainline protestant rate of adherence	117.54	105.76	95.00	84.26
Evangelical rate of adherence	215.62	217.04	226.67	229.57
Catholic rate of adherence	149.27	150.33	138.34	136.46
Orthodox rate of adherence	1.54	1.75	4.25	3.77
Other rate of adherence	25.89	24.75	31.67	29.00

Table 5: CCES benchmarking

	All counties in CCES	**Counties in our sample and in CCES**
Ideology (5 pt)	3.30	3.28
Party ID (7 pt)	3.91	3.88
Religious importance	3.11	3.11
Church attendance	3.28	3.27
Prayer frequency	5.02	5.00

Table 6: Presidential vote benchmarking

	All counties	**Counties in our dataset**
Obama vote 2008	44.9%	46.2%
McCain vote 2008	53.5%	52.3%
Turnout among registered voters	70.4%	70.9%

Table 7: Regional comparison of denominations (NCS)

	New England		**South**		**Midwest**		**West**	
	Our sample	*NCS*	*Our sample*	*NCS*	*Our sample*	*NCS*	*Our sample*	*NCS*
Baptist	16%	8%	19%	17%	46%	69%	27%	6%
Methodist	9%	9%	7%	26%	5%	56%	1%	10%
Lutheran	3%	14%	7%	61%	1%	15%	6%	11%
Presbyterian or Reform	5%	21%	5%	26%	2%	32%	2%	21%
Pentecostal	13%	9%	13%	22%	15%	48%	12%	21%

Table 8: Regional comparison of denominations (2010 Religious Census)

	Percent of congregations that are evangelical		**Percent of congregations that are mainline protestant**	
	2010 Religious Census	*SermonCentral*	*2010 Religious Census*	*SermonCentral*
Northeast	34%	56%	42%	20%
Midwest	50%	49%	35%	39%
South	65%	71%	21%	20%
West	50%	69%	18%	18%

Table 9: State-level comparison of denominations (2010 Religious Census)

			Our Sample						*2010 Religious Census*		
State	Sermon Count	Pastor Count	Mainline Pastors	Evangelical Pastors	Other Pastors	Mainline %	Evangelical %	Other %	Mainline %	Evangelical %	Other %
AK	424	13	1	12	0	0.08	0.92	0	0.17	0.53	0.3
AL	4251	175	39	108	28	0.22	0.62	0.16	0.16	0.67	0.17
AR	2217	131	21	98	12	0.16	0.75	0.09	0.14	0.72	0.14
AZ	2083	89	14	64	11	0.16	0.72	0.12	0.1	0.56	0.34
CA	4328	342	55	229	58	0.16	0.67	0.17	0.13	0.58	0.29
CO	1216	78	17	51	10	0.22	0.65	0.13	0.18	0.57	0.25
CT	251	25	4	18	3	0.16	0.72	0.12	0.31	0.34	0.35
DC	86	4	1	2	1	0.25	0.5	0.25	0.3	0.33	0.37
DE	149	16	5	9	2	0.31	0.56	0.13	0.33	0.44	0.23
FL	7202	300	57	203	40	0.19	0.68	0.13	0.13	0.66	0.21
GA	3845	227	41	158	28	0.18	0.7	0.12	0.18	0.65	0.17
HI	111	9	3	5	1	0.33	0.56	0.11	0.17	0.47	0.36
IA	1249	68	33	24	11	0.49	0.35	0.16	0.42	0.42	0.16
ID	330	22	7	11	4	0.32	0.5	0.18	0.1	0.36	0.53
IL	5782	211	63	117	31	0.3	0.55	0.15	0.26	0.51	0.23
IN	4891	176	56	89	31	0.32	0.51	0.18	0.27	0.59	0.13
KS	2061	69	14	36	19	0.2	0.52	0.28	0.31	0.53	0.17
KY	2734	158	46	89	23	0.29	0.56	0.15	0.19	0.71	0.1
LA	2990	121	19	92	10	0.16	0.76	0.08	0.13	0.6	0.27
MA	858	40	4	24	12	0.1	0.6	0.3	0.31	0.33	0.36
MD	910	75	15	41	19	0.2	0.55	0.25	0.32	0.47	0.22
ME	261	17	0	13	4	0	0.76	0.24	0.41	0.37	0.22
MI	3252	159	49	83	27	0.31	0.52	0.17	0.24	0.53	0.24
MN	866	65	24	32	9	0.37	0.49	0.14	0.33	0.47	0.2
MO	2796	152	41	95	16	0.27	0.63	0.11	0.2	0.63	0.16
MS	1307	113	29	75	9	0.26	0.66	0.08	0.2	0.62	0.18
MT	43	16	2	9	5	0.13	0.56	0.31	0.23	0.52	0.25
NC	3339	249	43	177	29	0.17	0.71	0.12	0.24	0.62	0.14
ND	178	16	4	7	5	0.25	0.44	0.31	0.45	0.36	0.19
NE	248	25	9	14	2	0.36	0.56	0.08	0.36	0.43	0.2
NH	79	13	0	7	6	0	0.54	0.46	0.4	0.34	0.26
NJ	995	69	19	41	9	0.28	0.59	0.13	0.31	0.33	0.36
NM	1276	29	4	23	2	0.14	0.79	0.07	0.12	0.54	0.34
NV	271	19	1	17	1	0.05	0.89	0.05	0.1	0.48	0.42
NY	2203	135	27	86	22	0.2	0.64	0.16	0.3	0.35	0.35
OH	5177	225	60	123	42	0.27	0.55	0.19	0.31	0.51	0.18
OK	4101	138	19	104	15	0.14	0.75	0.11	0.15	0.75	0.1
OR	1179	39	9	24	6	0.23	0.62	0.15	0.16	0.6	0.24
PA	3603	156	43	76	37	0.28	0.49	0.24	0.4	0.4	0.2
RI	48	9	1	6	2	0.11	0.67	0.22	0.31	0.3	0.38
SC	3526	122	20	78	24	0.16	0.64	0.2	0.21	0.6	0.19
SD	580	19	6	10	3	0.32	0.53	0.16	0.37	0.45	0.18
TN	4587	236	51	163	22	0.22	0.69	0.09	0.18	0.7	0.12
TX	7913	503	85	371	47	0.17	0.74	0.09	0.13	0.7	0.17
UT	260	11	3	5	3	0.27	0.45	0.27	0.02	0.08	0.9
VA	2073	149	26	107	16	0.17	0.72	0.11	0.3	0.56	0.14
VT	17	2	0	2	0	0	1	0	0.47	0.26	0.27
WA	1823	95	10	73	12	0.11	0.77	0.13	0.19	0.56	0.26
WI	831	58	21	29	8	0.36	0.5	0.14	0.3	0.48	0.22
WV	1956	65	11	41	13	0.17	0.63	0.2	0.44	0.47	0.08
WY	22	6	1	5	0	0.17	0.83	0	0.18	0.52	0.29

G Regression results

	(1) Gen. Politics	(2) Economy	(3) Abortion	(4) Homosexuality	(5) Civil Rights	(6) Welfare
Female	0.004	-0.056	0.057	-0.060	0.106	0.001
	(0.03)	(0.08)	(0.07)	(0.08)	(0.11)	(0.05)
White	-0.044*	-0.013	-0.079	-0.097	-0.070	-0.076**
	(0.02)	(0.07)	(0.05)	(0.06)	(0.06)	(0.03)
Baptist	0.021	-0.066	0.051	0.108**	-0.005	-0.025
	(0.02)	(0.06)	(0.04)	(0.04)	(0.05)	(0.03)
Evangelical	0.006	-0.048	0.011	0.099**	-0.088*	-0.049*
	(0.02)	(0.05)	(0.04)	(0.04)	(0.05)	(0.03)
Methodist (ML)	0.069***	0.192**	0.133***	-0.101	0.375***	0.265***
	(0.02)	(0.08)	(0.04)	(0.07)	(0.09)	(0.07)
Church of Christ	0.047	0.261***	0.058	0.153**	0.077	0.018
	(0.03)	(0.09)	(0.05)	(0.07)	(0.06)	(0.03)
Presbyterian	0.077**	0.291**	0.153*	0.294***	0.243**	0.094*
	(0.03)	(0.14)	(0.09)	(0.09)	(0.12)	(0.05)
Episcopalian	0.098	0.024	0.379***	-0.130	0.203	0.096
	(0.07)	(0.14)	(0.07)	(0.13)	(0.13)	(0.18)
Lutheran	-0.075	-0.042	-0.048	-0.251***	0.143**	0.048
	(0.05)	(0.06)	(0.06)	(0.09)	(0.07)	(0.06)
Geo: Pop. (ln)	-0.013	0.009	-0.035**	-0.020	0.009	-0.002
	(0.01)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)
Geo: White %	0.011	0.020	0.012	0.022	-0.014	0.001
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)
Geo: Income	0.012	0.015	0.022*	0.012	0.036	-0.001
	(0.01)	(0.02)	(0.01)	(0.02)	(0.03)	(0.02)
Geo: Obama 08 %	0.034***	0.023	0.058***	0.057**	0.069**	0.023
	(0.01)	(0.03)	(0.02)	(0.02)	(0.03)	(0.02)
Geo: South	0.013	-0.061	-0.006	-0.105***	0.039	0.054*
	(0.02)	(0.05)	(0.04)	(0.04)	(0.06)	(0.03)
Church Size (100-249)	0.061***	0.106**	0.081***	0.161***	0.076**	0.030
	(0.02)	(0.04)	(0.03)	(0.04)	(0.03)	(0.02)
Church Size (250-499)	0.048*	0.179***	0.110**	0.172***	0.095**	0.017
	(0.02)	(0.07)	(0.04)	(0.05)	(0.05)	(0.03)
Church Size (500-999)	-0.006	0.070	0.119	0.096	0.049	-0.001
	(0.03)	(0.07)	(0.10)	(0.08)	(0.05)	(0.04)
Church Size (1000+)	0.018	0.151	-0.080	0.371***	-0.071	0.051
	(0.05)	(0.11)	(0.06)	(0.07)	(0.07)	(0.07)
New Church	0.063*	0.106	0.050	-0.061	0.483***	0.100
	(0.04)	(0.08)	(0.06)	(0.10)	(0.18)	(0.08)
Constant	-1.368***	-3.997***	-4.448***	-3.970***	-4.293***	-4.241***
	(0.03)	(0.09)	(0.07)	(0.12)	(0.09)	(0.07)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Pastors	5,042	5,042	5,042	5,042	5,042	5,042
Locales	922	922	922	922	922	922
N	100,525	100,525	100,525	100,525	100,525	100,525
BIC	72657.1	16585.6	11999.7	13540.9	12406.2	12599.7

* p<0.10, ** p<0.05, *** p<0.010

Table 10: This table displays the results of the fractional logistic regression models. Standardized coefficients (log odds) and standard errors in parentheses. Non-standardized coefficients are displayed for dummy variables. Note that the baseline category for church size is 0-99 congregants. *New Church* measures whether a given church has been recently established.

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