Missionaries, Mechanisms, and Democracy

Preanalysis Plan

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1 Introduction

This document outlines a research plan for studying the causal mechanisms that characterize the effect of Conversionary Protestants (CPs) on the spread of liberal democracy. In an award-winning article published in the *American Political Science Review*, Woodberry (2012) demonstrates that CPs exerted a positive effect on democracy in the non-Western world. His identification strategy centers on two components: (1) an in-depth examination of the historical record with a focus on ruling out alternative explanations and (2) a quantitative analysis of data on 142 coun-

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tries, which includes a comprehensive suite of regression specifications showing that the positive association between CPs and democracy is quite robust. Importantly, Woodberry (2012) provides a great deal of discussion about the causal mechanisms underlying this relationship. However, he notes that his empirical analyses "demonstrate a causal association between Protestant missions and democracy, but do not test which mechanism is most important" (256).

In this research, we plan to pick up where Woodberry (2012) left off. We will build on his work by assessing the three central causal mechanism that he posits in his discussion of the historical record: (1) mass printing, (2) mass education, and (3) civil society. Specifically, we will use causal mediation analysis (Imai, Keele, Tingley, and Yamamoto 2011; Imai and Yamamoto 2013) to evaluate the relative importance of each factor, as defined by their estimated mediation effects and proportions of the causal effect that flow through each one. These three mechanisms represent the core of Woodberry's (2012) theoretical contribution. Thus, examining their relative importance is a critical component of a comprehensive test of his theory. Below we provide details on the causal model we plan to evaluate and a research design we intend to execute. We also discuss a plan of action for incorporating additional analyses that we do not yet foresee into our work.

2 Causal Model

Woodberry (2012, 256) summarizes the causal process between CPs and democracy in a stylized causal graph, which we reproduce as Figure 1. The graph depicts an intricate system that includes pretreatment covariates, the treatment itself, several mediating variables (i.e., mechanisms), and ultimately the outcome. The large number of causal arrows indicates a complex set of dependencies between the relevant factors, which is not surprising given the complexity of the topic. Indeed, in his review of the literature Woodberry (2012) discusses an enormous volume of research addressing the spread of liberal democracy. However, there is an inherent tradeoff between the theoretical process depicted in that graph and what is feasible with the empirical evidence. Thus, the causal process as represented by Woodberry's (2012) statistical models is somewhat simpler.

[Insert Figure 1 here]

We intend to analyze a simpler version of this model in our mediation analysis as well. While we plan to use the same set of pretreatment covariates as Woodberry uses (see below), we will focus our attention on the three causal mechanisms to which he emphasizes the most and devotes the most attention to in his discussion of the historical record: mass printing, mass education, and civil society (Woodberry 2012, 249–253). These are not the only mediating variables in Figure 1. However, they stand out as the most theoretically-motivated mechanisms among the various factors he considers. In fact, Woodberry largely discusses the other mediating variables drawn in Figure 1 within the context of these main three mechanisms. Thus, while the mediation process may actually be more complex, mass printing, mass education, and civil society represent a useful group of variables on which to focus as we seek to design a feasible study of causal mechanisms.

Figure 2 presents two causal graphs of the mediation process we intend to test. First consider panel (a). The treatment is Conversionary Protestants and the outcome is Democracy. Woodberry's (2012) data are observational, and so it is necessary to include pretreatment covariates to mitigate confounding. These covariates may affect the treatment, the mediators, and/or the outcome directly without threatening identification of mediation effects (Keele, Tingley, and Yamamoto 2015). The three mediating variables—mass printing, mass education, and civil society—fall between the treatment and outcome. Additionally, we draw an arrow between the treatment and the outcome to allow for the possibility of a direct effect.

[Insert Figure 2 here]

Figure 2, panel (a) represents a causal process in which we assume no association between the three mechanisms. This choice makes estimation more straightforward. However, that assumption may not always be realistic (Imai and Yamamoto 2013). One possible violation in this case might be that increased access to printed materials among the mass public in a given country caused an increase in mass education. Woodberry (2012, 251) actually makes the point that such an association does *not* exist in the historical record, so our simpler model in panel (a) may be appropriate. Nonetheless, we also plan to consider a more complicated process—shown in panel (b)—in which

we relax the assumption of no association between printing and education. Throughout our analyses we maintain that civil society is distinct from the other mechanisms, and thus we assume its independence, conditional on the covariates.[1]

3 Research Design

Here we describe our empirical strategy for testing the causal models presented in Figure 2. In brief, our plan is to start with Woodberry's (2012) original regression analyses, then add the mediation analysis. We will use the same variables, coding decisions, estimation methods, and other choices as described in Woodberry (2012).[2] We adopt this approach because the primary goal of this research is to build on Woodberry's work. Moreover, we want our results to be as comparable as possible to Woodberry's results. Thus, we define the set of choices Woodberry made as the status quo.

As of the original deposit date of this document (June 7, 2018), we have acquired Woodberry's (2012) replication data and successfully replicated the exact results he presents in the article. We have also collected additional data and made choices about the new analyses we plan to conduct, which we discuss below. We have *not* yet conducted any mediation analyses. Thus, our plan for conducting this research is results-blind.

3.1 Data

Woodberry's (2012) outcome variable is a country's mean democracy score during the period 1950–1994, scaled from 0–100 (with higher scores indicating higher levels of democracy). The data come from the Cross-national Indicators of Liberal Democracy series (see Paxton 2002; Bollen 2009). Woodberry (2012) selects this measure because it includes a broader range of countries than alternatives and minimizes rater bias (Woodberry 2012, 257).

3.1.1 Pretreatment Covariates and Treatment

Woodberry (2012) collects several pretreatment covariates to include in his regression models.[3]

[1] We will empirically assess the between-mediator associations for all three mechanisms and the consequences of those associations for our mediation estimates. See our discussion of robustness checks below.

[2] We will report any deviations from this approach in our final manuscript and/or in updates to this document.

[3] Some of the covariates are not actually pretreatment as defined by measurement. For example, the treatment

Briefly, these covariates account for alternative theories of the spread of democracy, exogenous and precolonial conditions, other factors that influenced colonizers and missionaries, and endogenous or intervening variables (see Woodberry 2012, 257–258). Finally, he includes a set of "mission variables." Some of these variables are covariates, such as foreign Catholic priests per 10,000 population in 1923 and years exposure to Catholic missions. The remaining measures in this group relate to Protestant missions and comprise the set of variables of primary theoretical interest: percent Evangelized by 1900, years exposure to Protestant missions, and Protestant missionaries per 10,000 population in 1923.

While we include all of the mission variables in our analyses, we use this latter variable, Protestant missionaries per 10,000 population in 1923, as our treatment. It is preferable to the other two candidates (percent Evangelized and years exposure) because it is the most direct measure of the presence of CPs in a country. The percent Evangelized measure includes converts to Catholicism in it (Woodberry 2012, 257) and years exposure measures the earliest time at which CPs were present in a country rather than levels of CPs in that country (Woodberry 2012, 263).[4]

3.1.2 Mediators

Our mediator variables are designed to test the three causal mechanisms discussed above. We rely on a combination of data collected by Woodberry and our own data collection for these variables. These efforts yielded multiple candidates for each mechanism. We plan to complete analyses with all of them, as we describe here.

The first mediator is mass printing, which Woodberry (2012) primarily discusses as enhancement to the public sphere via the expansion of newspapers (249). Although he does not employ it in his main analyses, Woodberry's data include a measure of this conceptualization: an indicator of average daily newspaper circulation per 1,000 population in 1975, 1980,1985, and 1990.[5] We

variable we select (see below) reflects measurement in 1923, but percent European is measured in 1980 and percent Muslim in 1970. While posttreatment bias is a serious one (Montgomery, Nyhan, and Torres 2018), we choose to bracket this issue entirely because the inclusion of these variables was a choice made by Woodberry. We place a very high premium on avoiding any deviations from the original specifications except for the addition of our mediation analysis.

[4]Specifically, Woodberry (2012) measures this variable as $1960 - y_c$, where y_c is the first year in which CPs arrived in country c (263).

[5]These variables come from the United Nations (UN) Data (see http://data.un.org/).

compute the means across these four years to construct a mass printing mediator variable. The measure itself is internally valid; however, the timing is not ideal. Measurement does occur post-treatment (i.e., after 1923), but it also falls after the measurement of the outcome begins (1950). Accordingly, we also plan to consider an indicator that can be measured earlier: the number of book titles per capita (Fink-Jensen 2015).[6] This variable is useful in that it can be measured in the 1924–1949 period that separates treatment and outcome. However, the data have a much larger amount of missingness for Woodberry's sample of countries than Woodberry's newspaper data (see Table 1 and discussion below).

Next, we consider mass education as a mediating variable. Woodberry's data also contain a candidate measure, which he uses in some robustness checks (Woodberry 2012, Table 5, 265). Specifically, his data include the mean enrollment in secondary education from 1960–1985 (Barro and Lee 1994). However, this variable does not cover all of the countries in his full sample and is also partially concurrent with the democracy outcome. As an alternative, we gathered education data from the Varieties of Democracy Project (V-Dem, see Coppedge et al. 2018). V-Dem provides data on the percentage of a country that is literate (from Vanhanen 2003), the average years of education for citizens older than 15, and a Gini-type measure of educational inequality. Each of these variables are available at least as early as 1924.

We consider the percentage literate variable to be a particularly promising mediator variable for both theoretical and empirical reasons. Theoretically, it matches Woodberry's (2012) argument that CPs sought to provide education to spread literacy so that individuals could read the Bible themselves (246, 249). This literacy, in turn, promoted democracy (Woodberry 2012, 251). Empirically, the literacy data cover more countries than Woodberry's secondary education enrollment data. The average years of education variable allows a more detailed measurement of education levels compared to Woodberry's measure, particularly for countries with relatively few individuals who receive secondary education. However, this variable suffers from a large amount of missing data for Woodberry's sample of countries when compared to the literacy variable. Finally, the

[6]This measure is available at https://www.clio-infra.eu/Indicators/BookTitlesperCapita.html.

educational inequality variable allows us to examine a slightly different aspect of mass education that Woodberry proposes. He argues that CPs spread education to non-elites, reducing educational inequality (Woodberry 2012, 251). However, this variable also suffers from more missing data than the literacy data.

Finally, civil society is the third causal mechanism we consider. Although the development and spread of voluntary organizations, nonviolent protest, and other political movements is a key element of Woodberry's (2012) theoretical framework (e.g., 252–253), he does not include any such measure in his analyses or replication data. To obtain one, we again turn to V-Dem (Coppedge et al. 2018). V-Dem provides a civil society participation index that captures the extent to which citizens are involved in CSOs, how much CSOs are consulted by policy makers, whether women participate in CSOs, and whether political candidate nomination is decentralized (Coppedge et al. 2018). This variable is highly suitable to serve as a mediator because it provides a robust measurement of the civil society that Woodberry claims connects CPs with the development of democracy and covers the vast majority of the countries in the estimation sample (Woodberry 2012, 252–253).

As our discussion above makes clear, the key issue that we must address with all of these possible measures of causal mechanisms is missing data. Our objective is to use Woodberry's full sample of data in our mediation analyses. His measurement strategy involves computing several variables by averaging over a span of years; for instance, his outcome variable is a mean over the period 1950–1994. We adopt this approach in constructing our mediators. However, the historical nature of the data means that some countries did not exist or were known by different names when our various mediators were measured.[7] Consequently, we consider two options when constructing mediators: compute the averages from (1) 1924–1949 or (2) 1924–1994. The former approach best matches the temporal nature of a mediator because it occurs between treatment (1923) and outcome (1950). However, it yields more missing data. In contrast, the second strategy overlaps measurement of the outcome, but allows for more data to be collected. We plan to conduct

[7] See Woodberry (2012, 257) for a discussion of how he addresses this issue in measuring the outcome variable.

our analyses using both measurement strategies to assess the robustness of our results. Table 1 summarizes our mediator data collection efforts.

[Insert Table 1 here]

For those data values we cannot fill in, we plan to use multiple imputation with the Amelia II software available in R (Honaker, King, and Blackwell 2011). Amelia begins with the assumption that the complete data are distributed multivariate normal, then employs the expectation-maximization (EM) algorithm to impute the missing values. It repeats this process m times (we plan to use the default of $m = 5$), then analysis continues as usual with those m complete datasets. An adjustment to measures of uncertainty is also necessary (see Blackwell, Honaker, and King 2017, 309).[8] We will use the complete data from Woodberry's sample to impute the missing values in our mediators.[9] Amelia also includes diagnostic functions for checking the imputation results. We plan to use these tools to ensure the validity of our imputed mediators before proceeding to our main analyses.

3.2 Specification Selection

Woodberry's (2012) empirical analysis is comprised of 32 reported regression models, with many more in the replication files. For purposes of feasibility, we must simplify before proceeding to the mediation analysis. Based on its comprehensive nature and Woodberry's (2012) discussion of the empirical results, we regard his Model 4 from Table 3 (262) as the "Canonical Model."[10] This model is estimated on his full sample of 142 countries and includes several groups of covariates (though not every single covariate available). Moreover, among the models he reports that are

[8] We will perform this adjustment according to the following steps, as discussed by Blackwell, Honaker, and King (2017, 309). First, we will simulate our quantities of interest from the mediation models with each of the m datasets via bootstrapping and/or quasi-Bayesian replicates (see Tingley, Yamamoto, Hirose, Keele, and Imai 2014). Second, we will combine the simulation replicates as if they came from the same model. Finally we will summarize the combined vectors of simulated replicates to report the results (see also King, Tomz, and Wittenberg 2000; Imai, King, and Lau 2008).

[9] We do not need to impute any data from the covariates that Woodberry (2012) includes in his regressions. We only need to impute data in the mediators.

[10] Another candidate model is Table 2, Model 3 (Woodberry 2012, 260). We favor Table 3, Model 4 because it includes covariates measuring the process of colonization (Woodberry 2012, 262–263). However, we plan to assess the robustness of our results using Table 2, Model 3 (see below).

estimated on the full sample, this model produces the second-largest adjusted-R^2 value.[11] Thus, it is a good representation of the statistical and substantive results that Woodberry communicates in his research. We focus our analyses on this model.

The Canonical Model reports a positive and statistically significant treatment effect of 4.43 (confidence interval: [1.28, 7.59]). Recall that the outcome variable is scaled from 0–100. The estimate indicates that, all else equal, a standard deviation increase in Protestant missionaries is associated with a 0.26 standard deviation increase in a country's average democracy score. Woodberry highlights the substantive significance of this result throughout his discussion. In brief, while there are many factors that affected the spread of democracy, the effect of CPs is strong enough that it deserves serious scholarly attention.

3.3 Estimation

Woodberry (2012) employs various linear regression estimators in his analyses, including ordinary least squares (OLS), robust regression (RR), and instrumental variables (IV). He estimates the Canonical Model with RR due to concerns with skewness and outliers in some of the covariates (Woodberry 2012, 259). This estimator uses iteratively reweighted least squares (IRLS) to weight observations based on their outlyingness (e.g., Street, Carroll, and Ruppert 1988). We plan to use Stata's implementation of the estimator as Woodberry (2012) did to maintain comparability to the original results. We plan to conduct the mediation analysis using the mediation package in R (Tingley et al. 2014).[12]

3.3.1 Main Analyses

We plan to focus on two main analyses. First, we will estimate the causal mediation effect of each mediator separately. This approach is consistent with the causal graph in Figure 2, panel (a), in which we assume no association between the mediators. Our key quantities of interest in this

[11] The adjusted-R^2 reported in Table 3, Model 5 is somewhat larger (0.496 versus 0.467). However, Model 5 is incorrectly specified because it omits some constituent terms of interaction effects (Brambor, Clark, and Golder 2006).

[12] We can use Stata's implementation of RR in R by estimating the model in Stata and saving the weights generated by the estimator, then using those weights in a standard OLS estimation in R. This approach reproduces the coefficients from Stata exactly, although the standard errors are off. We plan to employ bootstrapping and/or robust standard errors in the mediation analysis to correct this issue.

analysis will be the average causal mediation effect (ACME), which is the effect that flows through the mediator, and the proportion mediated (PM), which indicates the relative size of the ACME to the total effect (Tingley et al. 2014). We plan to (1) compare PM values for each mediator and (2) formally test the null hypothesis that the three ACMEs are equal to each other using the $\alpha = 0.05$ threshold for statistical significance.

Second, we will repeat the first analysis, but allow for the possibility of association between mass printing and mass education. This association is reflected in the causal graph depicted in Figure 2, panel (b). To complete this analysis we will use the sensitivity analysis approach recommended by Imai and Yamamoto (2013). The key quantities of interest will remain the same as in the first analysis.

3.3.2 Additional Robustness Checks

In addition to our main analyses, we also plan to conduct the following robustness checks and alternative specifications. We will most likely report these results in an appendix to our final manuscript.

- **Second model specification**. We will repeat our main analyses using the specification in Woodberry's (2012) Table 2, Model 3 (260).
- **Alternative treatment variables**. We will repeat our main analyses with Woodberry's other primary variables of interest—percent Evangelized by 1900 and years exposure to Protestant missions—as the treatment variable.
- **Additional covariates**. We will repeat our main analyses after including two covariates that Woodberry includes in other specifications, but does not include in the Canonical Model: economic development (operationalized as logged gross domestic product [GDP] per capita) and settler mortality (Acemoglu, Johnson, and Robinson 2001).
- **Additional mediator measures**. We will repeat our main analyses with all of the measures of each mediator described above.
- **Subsetting by region**. We will repeat our main analyses in several regions of the world discussed by Woodberry (Africa, Latin America, Asia, and Oceania).

- **Subsetting by colonizer**. We will repeat our main analyses after grouping countries by colonizer according to Woodberry's definitions (British, Catholic, other religious liberty colonies, Dutch, not colonized).
- **Omitting multiple imputation**. We will reduce the sample to only the cases for which we have mediator data without using multiple imputation and repeat the main analyses.
- **Sensitivity to covariates**. We will conduct sensitivity analyses on the possibility of an unmeasured confounding pretreatment covariate (Imai et al. 2011).
- **Sequential ignorability**. We will conduct sensitivity analyses that allow each mediator to be associated with the other mediators (Imai and Yamamoto 2013).

4 Updates

The original version of this plan was deposited on June 7, 2018. We plan to update it as needed over the course of the project. If we make any changes to our analysis after depositing this document, we will explain and justify those changes here.

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Figure 1: Stylized Causal Graph of the Effect of Conversionary Protestants on the Spread of Liberal Democracy (Woodberry 2012, Figure 1, 256)

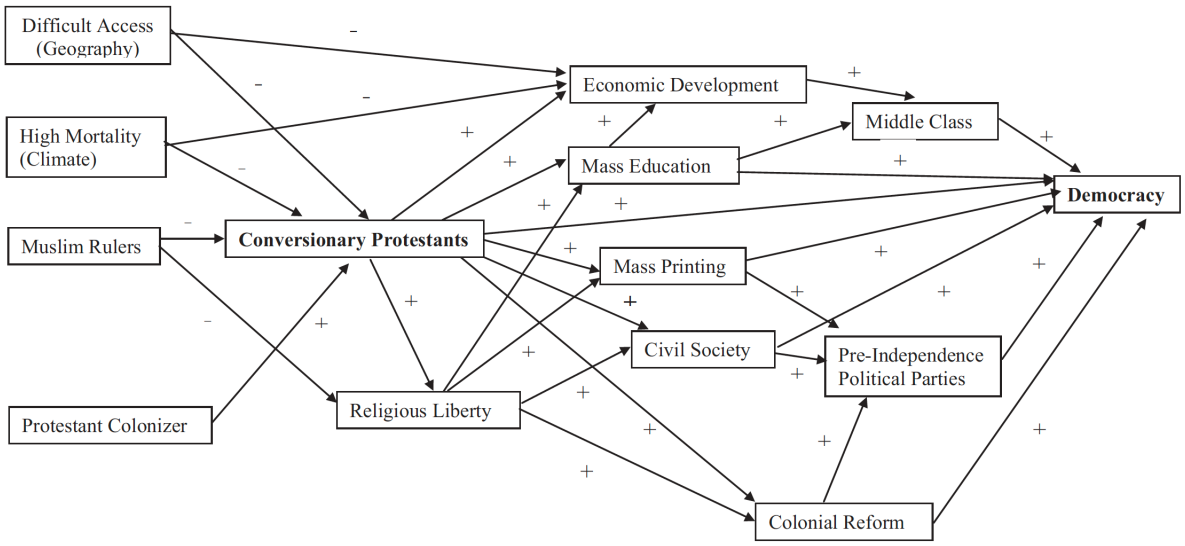
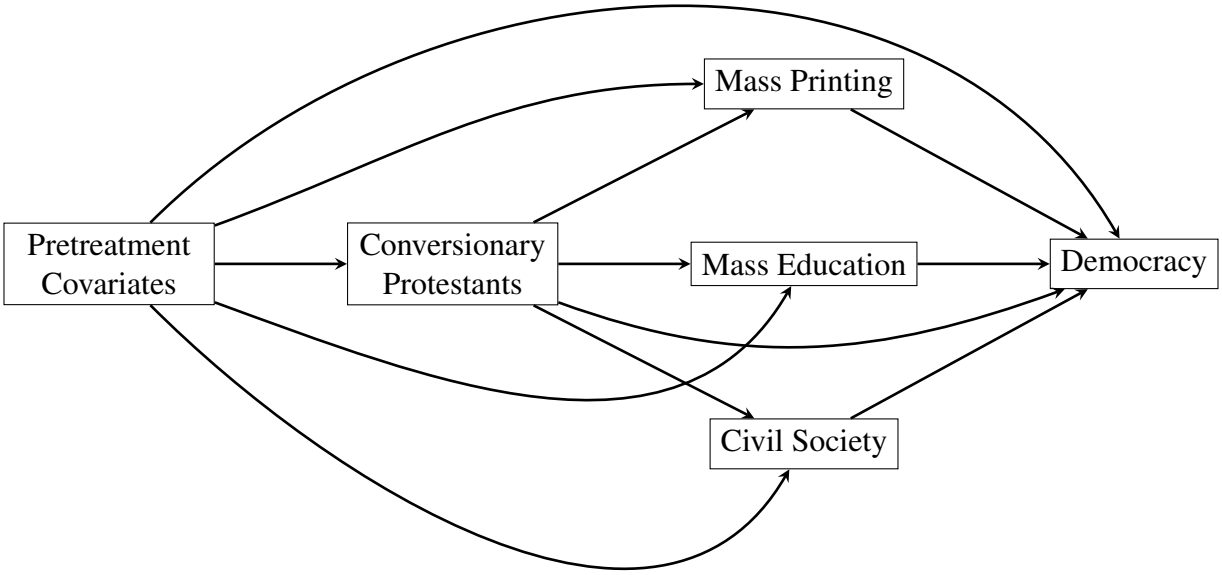


Figure 2: Proposed Causal Graph for Empirical Evaluation of the Mechanisms

(a) No Mediator Association



(b) Association Between Printing and Education

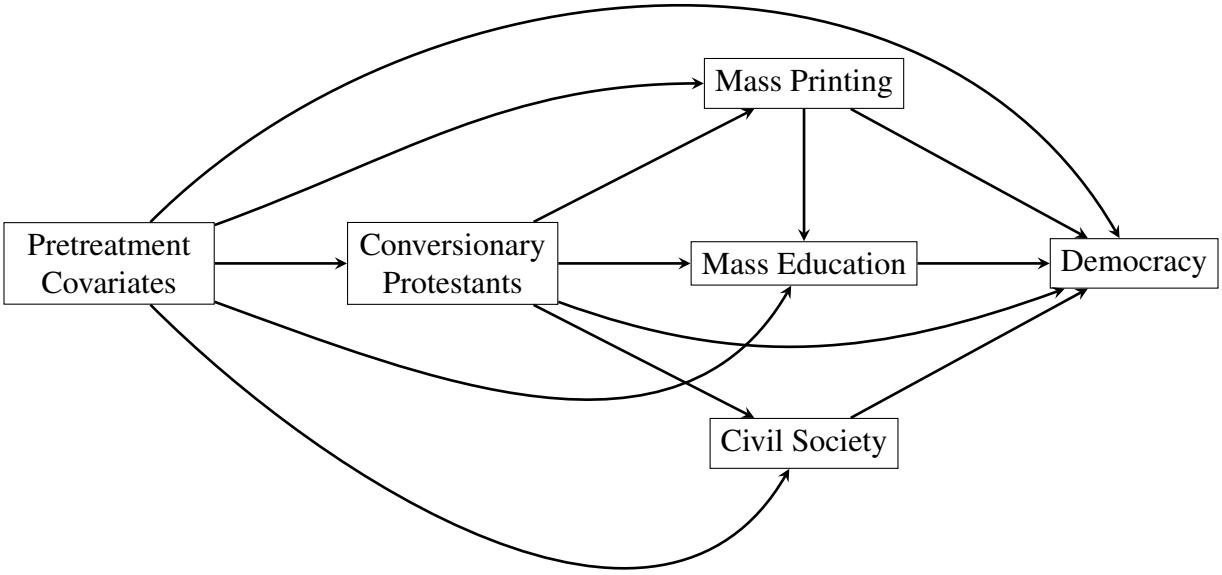


Table 1: Missingness in the Proposed Measures of Causal Mechanisms

Mediator	Variable	Source	Cases Missing	% Missing
Mass Printing	Mean daily newspaper circulation (average of 1975, 1980, 1985, 1990)	Woodberry (2012), UN Data	24	16.9
	Mean book titles per capita (average)	Fink-Jensen (2015)	129/112	90.8/78.9*
Mass Education	% Literate (average)	Vanhanen (2003); Coppedge et al. (2018)	96/32*	67.6/22.5*
	Mean years education (average)	Coppedge et al. (2018)	77/42*	54.2/29.6*
	Secondary school enrollment (1960–1985)	Woodberry (2012)	57	40.1
	Gini educational inequality (average)	Coppedge et al. (2018)	76/42*	53.5/29.6*
Civil Society	Civil society participation index (average)	Coppedge et al. (2018)	27/18*	19.0/12.7*

Note: Cell entries summarize missing data in the mediator measures. The percentage missing for each variable is computed based on the 142 countries in the estimation sample of Woodberry's (2012) Table 3, Model 4 (262). * Pairs of entries denoted ·/· indicate the two measurement strategies discussed in the text: computing the averages from 1924–1949 (listed first) or 1924–1994 (listed second).