The Determinants of Wealth Inequality: War, Finance, and Redistribution*

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Abstract

We examine the determinants of wealth inequality using Bayesian model averaging to address regression model uncertainty stemming from the lack of encompassing model of wealth inequality. The methodology is perfectly suitable for situations where the there is a lot of potential explanatory variables and there is no unifying theoretical framework. We use global sample of 67 countries and include nearly 40 different determinants of wealth inequality capturing various economic, political, financial, institutional, and geographical indicators. Moreover, we specifically explore the role of financial sector by including several financial indicators to capture the multidimensionality of financial sector and we assess whether distinct characteristics of financial sector exhibit different effects on wealth inequality. The wealth inequality data are from yearly Credit Suisse Wealth Report and we rely on Global Financial Development Database by the World Bank for data on financial indicators. Our results confirm that financial sector exerts a complex effect on wealth inequality. While greater financial depth increases inequality, better access to finance decreases it. Redistribution of income and foreign direct investment are associated with lower inequality. On the contrary, wars, trade openness, and technological progress contribute to greater inequality.

Keywords: Wealth inequality, Bayesian model averaging

JEL Codes: D31, E21

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1 Introduction

Economic inequality increasingly draws attention of researchers in the field. With new data available owing to, for example, Piketty (2014) and Davies et al. (2011, 2016), we have a chance to shed new light on what we know about inequality. Their work offers fresh perspective as they provide the evidence on inequality of wealth rather than income. The evidence brought forward has severe impact on our thinking as the levels of inequality derived from wealth distribution are distinctively higher than those based on the distribution of income. Moreover, the countries traditionally considered quite egalitarian exhibit much higher inequality levels when we consider wealth instead of income.

In contrast with the twin concept of income inequality, the theoretical understanding of wealth inequality is limited. Much debated concept of $r > g$ suggested by Piketty (2014) received strong criticism from the theoretical point of view (Blume and Durlauf, 2015; Mankiw, 2015; Rowthorn, 2014; Soskice, 2014).[1] The principle framework thus remains in the scope of dynamic quantitative models making use of the heterogeneity of returns, preferences, transmission of human capital, and bequests. Fella and De Nardi (2017) offer an overview of these models and their ability to mirror empirical wealth distribution. One of the conclusions is that all the models critically rely on the saving motives of individuals. Indirect theoretical predictions about wealth inequality arise from the model by Pástor and Veronesi (2016), where inequality depends on the skill and risk aversion of entrepreneurs, taxation, and development of financial markets[2]. Empirical evidence on wealth inequality along with its determinants is an entirely unexplored territory with a rare exceptions of fitting the data to the theoretical models presented earlier.

Why is wealth inequality higher in the United States than United Kingdom? And why is wealth distribution in Slovenia much less unequal than in Germany? To the best of our knowledge, all the empirical studies up to date focus on the issues of measurement and development of wealth inequality in time (Alvaredo et al., 2013; Piketty and Zucman, 2014; Saez and Zucman, 2016) and disregard the question of driving forces in the background. In this paper, we build upon these studies and address potential determinants of wealth distribution relying on a global sample of countries. To capture wealth inequality, we use wealth Gini coefficient from Credit Suisse Wealth Databook (CSWD) constructed on the basis of methodology by Davies et al. (2016). We supplement this data with numerous potential determinants of wealth inequality. In addition, we also add a subset of the most densely available series from Global Financial Development Database (GFDD) to capture various characteristics of financial systems. We include these to reflect the assumptions made by the theory where savings, which are necessarily dependent on financial markets, and financial development stand as the main drivers of wealth inequality.

We employ Bayesian Model Averaging (BMA) as our methodological framework. BMA is an established approach within the statistical theory (Koop et al., 2007; Raftery et al., 1997) and conveniently addresses the intrinsic model uncertainty present in the cross-country regressions

[1]See King (2017) for an excellent review of the literature on the topic.
[2]More specifically, the ability of entrepreneurs to diversify away their idiosyncratic risk.

(Durlauf et al., 2008; Fernandez et al., 2001). With the lack of encompassing model of wealth inequality, this is the preferred approach to reflect as many determinants of wealth inequality as possible in a unifying manner. In essence, BMA procedure evaluates different combinations of explanatory variables and weights the corresponding coefficients using the measure of model fit. In addition, BMA is the perfect tool for evaluation of numerous regressors and estimating their Posterior Inclusion Probability (PIP), the probability that they are relevant in explaining the dependent variable. Following the empirical literature on income inequality[3], we aim to deal with potential endogeneity within in the estimation by using lagged values of explanatory variables.

We make contribution to the literature in three key aspects. First, we run an empirical inquiry into the determinants of wealth inequality. This is an unprecedented effort differentiating the paper from the preceding work. Second, we employ BMA to address model uncertainty present in the standard regression models. Given the diverse and fragmented theoretical background of inequality, this issue is also relevant for the related concept of income inequality and is traditionally abstracted from. Third, we admit the multidimensionality of financial systems and include diverse characteristics of financial development among our explanatory variables.

Examining the cross-section of 67 countries, we identify that national savings, political stability, access to financial services, and redistribution are among the most important drivers of wealth inequality. This is overwhelmingly in accord with the predictions of the theoretical models. Saving, proxied by net national savings, increases wealth inequality along with the number of war years between 1950 and 2009. Openness and technological advancement also widens the gap between the wealthy and poor, corresponding to the suggestions made by Dabla-Norris et al. (2015) for income inequality drivers. At the same time, redistribution, measured by the difference between market and after-tax income Gini coefficient, access to finance, captured by the number of bank branches per 1000 inhabitants, and foreign direct investment are associated with lower levels of inequality.

The remainder of the paper is organized as follows. Section 2 presents the data.Section 3 introduces the BMA. We provide the results in section 4 and conclude in section 5. Robustness checks are available in the Appendix A.

2 Data

We construct a rich dataset of 67 countries and 37 explanatory variables that we believe might be affecting the wealth distribution. The selection is based on the theoretical predictions of wealth determinants as well as on the experiences from the papers studying income inequality. Our methodological choice allows us to be generous with the inclusion of regressors and therefore we can capture variety of different country characteristics. Our dependent variable is Gini index based on wealth distribution coming from a yearly CSWD based on the methodology of Davies et al. (2011, 2016).[4] They use the methodology to estimate the world distribution

[3]E.g. de Haan and Sturm (2017).

[4]This dataset has been recently used by Anand and Segal (2017)

of wealth and consequently provide estimates for individual countries. We take the average of available observations of the index (2010-2016) as the individual yearly observation may be affected by year-on-year stock market capitalization swings or significant changes in valuation of non-financial assets.

We supplement the data on wealth by large number of potential variables which could be driving inequality. These cover economic, financial, institutional, political, as well as social and cultural aspects of the countries in our sample. We also average the data over the period of their availability. This is typically from 1980 to 2009. Complete list of the explanatory variables along with their description and sources is available in Appendix A.

Our particular focus is on financial development, whether and how it affects the distribution of wealth within the economy in particular. Using the GFDD by the World Bank, we identify 7 different measures that reflect a multidimensionality of financial systems. Cihak et al. (2013) Describe 4 main dimensions of financial systems: depth, efficiency, stability, and access. We select the most densely series at out disposal reflecting aforementioned dimensions. GFDD also allows to distinguish not only between the different dimensions, but also to ascribe these characteristics separately to banking sector and financial markets. With the exception of stability and access, where we only control of variables representing banking due to data limitations, we take advantage of this distinction in our analysis. Table 2 presents descriptive

Table 1: Descriptive statistics of financial variables

	Min	Max	Mean	Std. dev
Net interest margin	0.66	12.81	4.87	3.04
Loans/deposits	40.11	181.56	103.19	28.87
Bank Z-score	-1.34	36.56	10.65	7.38
Private credit	4.71	137.48	44.24	29.95
Bank branches	1.45	101.16	22.71	20.34
Market capitalization	0.78	183.97	37.76	40.05
Market turnover	1.07	256.95	43.82	47.69

Table 2: Descriptive statistics of financial variables

Net interest margin	1.00						
Loan-to-deposits	-0.54	1.00					
Bank Z-score	-0.18	-0.06	1.00				
Private credit	-0.80	0.55	0.19	1.00			
Bank branches	-0.43	0.35	-0.11	0.46	1.00		
Market capitalization	-0.35	0.19	0.18	0.58	0.13	1.00	
Market turnover	-0.22	0.27	0.12	0.19	0.19	0.03	1.00

statistics while table 1 shows a correlation matrix of our financial variables. It is important to realize that contrary to common perception, the correlations between financial variables is far from perfect, with the only exception of net interest margin (a measure of banking sector efficiency) and credit available to the private sector (a measure of banking sector depth). This gives grounds to the distinction we make between the series and supports the idea of searching for the variables which would most precisely capture the functions of the financial systems postulated by the theory.

3 Bayesian Model Averaging

We describe our methodological approach, the BMA, in this section and draw heavily on Hasan et al. (2018). The application of BMA is particularly fruitful when there is an uncertainty regarding the specification of regression model, for example, when there are competing theories all suggesting a different regression model. Researchers typically specify some general regression model and sequentially eliminate the least significant explanatory variables to obtain the "best" model. This process, however, poses risk that some relevant explanatory variables are eliminated and there is no guarantee that researcher ends up with the "true" model. Koop (2003) shows that the risk of arriving to the model different from such model increases with the number of sequences of eliminating the least significant variables. On the other hand, BMA does not select the "true" model but, as its name suggests, averages all possible regression models assigning greater weight to "better" models based on their likelihood. Therefore, the BMA addresses the regression model uncertainty inherent to many economic theories.

To illustrate the BMA, consider a following linear model:

$$y = \alpha + X\beta + \varepsilon \qquad \varepsilon \sim \; N(0, \sigma^2 I) \tag{1}$$

where y is a dependent variable, α is a constant, X is the matrix of explanatory variables, β represents the corresponding coefficients, and ε is a vector of normally distributed IID error terms with variance σ^2.

BMA considers all possible combinations of X from equation 1 and takes a weighted average of the coefficients. Given that the combination is typically extremely high number and even with modern computers it is impossible to estimate all these regression models, researchers consider only a subset of models, see the remarks on the MCMC sampler below. The substructure of the model can be captured as follows:

$$y = \alpha_i + X_i\beta_i + \varepsilon \qquad \varepsilon \sim \; N(0, \sigma^2 I) \tag{2}$$

Here, X_i is a subset of X and α_i and β_i are the corresponding coefficients. Assuming that the total number of possible explanatory variables is K, the total number of models is equal to 2^K and $i \in [1, 2^K]$. It follows from Bayes' rule that

$$p(\beta|y, X) = \frac{p(y, X|\beta)p(\beta)}{p(y, X)} \tag{3}$$

where $p(\beta|y, X)$ is the posterior density, $p(y, X|\beta)$ is the marginal likelihood (ML), also known as the data generating process, $p(\beta)$ is the prior density, and $p(y, X)$ is the probability of the data. In the BMA, we essentially compare numerous different models $M_1, ..., M_i$. Assuming K possible regressors as discussed above, we have $M_1, ..., M_i$, where $i \in [1, 2^K]$. Given the Bayesian logic whereby we formally define the model using a likelihood function and a prior density, M_i depends on the parameters β_i, and their posterior probability can be derived as follows:

$$p(\beta_i|M_i, y, X) = \frac{p(y|\beta_i, M_i, X)p(\beta_i|M_i)}{p(y|M_i, X)} \tag{4}$$

The following subsections describe the averaging principle of BMA and individual components of equation 3.

Posterior Model Probability

The posterior model probability (PMP) is fundamental to the BMA framework, as it provides the weights for averaging model coefficients across submodels. PMP also arises from Bayes' theorem:

$$p(M_i|y, X) = \frac{p(y|M_i, X)p(M_i)}{p(y|X)} \tag{5}$$

where $p(y|M_i, X)$ is the marginal likelihood (ML) of the model (i.e., the probability of the data given the model M_i), $p(M_i)$ is the prior model probability, and $p(y|X)$ is the integrated likelihood. The term in the denominator is typically disregarded, as it is constant across all models under consideration. The PMP is then directly proportional to ML and the prior probability. A popular practice is to set the prior probability $p(M_i \propto 1)$ to reflect the lack of knowledge regarding the true model.

$$p(M_i|y, X) \propto p(y|M_i, X)p(M_i) \tag{6}$$

We discuss the calculation of ML in detail in section 3. The model prior needs to be elicited by the researcher and reflects the initial beliefs before inspecting the data.

Posterior Mean

Point estimates of the model parameters are often the focus of research, and it is possible to derive them within the Bayesian framework. Zeugner (2011) and Moral-Benito (2012) assert that the weighted posterior distribution of any statistic (most notably the β coefficients) is obtained using the following:

$$p(\beta|y, X) = \sum_{i=1}^{2^K} p(\beta_i|M_i, y, X)p(M_i|y, X) \tag{7}$$

where $p(M_i|y, X)$ is the PMP of the corresponding model M_i from equation 5. The point estimates can be acquired by taking expectations across the equation:

$$E(\beta|y,X) = \sum_{i=1}^{2^K} E(\beta_i|M_i,y,X)p(M_i|y,X) \tag{8}$$

Here, $E(\beta|y,X)$ is the averaged coefficient and $E(\beta|M_i,y,X)$ is the estimate of the β_i coefficients from model M_i. The posterior distribution of the coefficients is dependent on the choice of the prior g. Zeugner (2011) expresses the expected value of the parameter in M_i as follows:

$$E(\beta_i|y,X,g,M_i) = \frac{g}{1+g}\hat{\beta}_i \tag{9}$$

with $\hat{\beta}_i$ representing the standard OLS estimate.

Posterior Variance

Moral-Benito (2012) presents a formula for variance corresponding to the expected values of coefficients derived in the previous section:

$$\begin{aligned} Var(\beta|y,X) &= \sum_{i=1}^{2^K} p(M_i|y,X)Var(\beta_i|M_i,y,X) \\ &+ \sum_{i=1}^{2^K} p(M_i|y,X)(E(\beta_i|M_i,y,X) - E(\beta|y,X))^2 \end{aligned} \tag{10}$$

The variance consists of the weighted average of variance estimates across different regression models $Var(\beta_i|M_i,y,X)$ and the weighted variance across different models captured in the second component $E(\beta_i|M_i,y,X) - E(\beta|y,X))^2$. $E(\beta|y,X)$ is the posterior mean from equation 8. As a consequence, this may result in uncertainty regarding the parameter estimates due to the substantial differences across models even if the estimates of individual models are highly precise. Zeugner (2011) shows how the value of the prior g affects the posterior variance of the parameters:

$$Cov(\beta_i|y,X,g,M_i) = \frac{(y-\bar{y})'(y-\bar{y})}{N-3}\frac{g}{1+g}\left(1 - \frac{g}{1+g}R_i^2\right)(X_i'X_i)^{-1} \tag{11}$$

where $\bar{y}$ is the mean of vector y, N is the sample size and R_i^2 is the R-squared of model i.

Marginal Likelihood

ML can be calculated using equation 4 for each M_i. We need to integrate both sides of the equation with respect to β_i, employ $\int_\beta p(\beta_i|M_i,y,X)\,d\beta_i = 1$, and rearrange to arrive at

$$p(y|M_i,X) = \int_\beta p(y|\beta_i,M_i,X)p(\beta_i|M_i,X)\,d\beta_i \tag{12}$$

The above equation illustrates the general textbook derivation, but the computation depends on the elicited priors. Zeugner (2011) employs the "Zellner's g prior" structure, which we utilize in this paper. The ML for a single model can then be expressed using the prior as in Feldkircher and Zeugner (2009):

$$p(y|M_i, X, g) = \int_0^\infty \int_\beta p(y|\beta_i, \sigma^2, M_i)p(\beta_i, \sigma^2|g)\, d\beta d\sigma \tag{13}$$

Furthermore, the authors assert that ML is in this case simply proportional to

$$p(y|M_i, X, g) \propto (y-\bar{y})'(y-\bar{y})^{-\frac{N-1}{2}}(1+g)^{-\frac{k_i}{2}}\left(1-\frac{g}{1+g}R_i^2\right)^{-\frac{N-1}{2}} \tag{14}$$

In this equation, R_i^2 is the R-squared of model M_i, and k_i is the number of explanatory variables in model i introduced to include a size penalty for the model. N and $\bar{y}$ are the same as in equation 11, the number of observations and the mean of vector y, respectively.

Posterior Inclusion Probability

The standard BMA framework reports the PIP, which reflects the probability that a particular regressor is included in the "true" model. PIP is the sum of the PMPs of the models including the variable k in question:

$$PIP = p(\beta_k \neq 0|y, X) = \sum_{i=1}^{2^K} p(M_i|\beta_k \neq 0, y, X) \tag{15}$$

Priors

The BMA methodology requires determining two types of priors: g on the parameter space and $p(M_i)$ on the model space. The priors are crucial in determining the posterior probabilities (Feldkircher and Zeugner, 2009; Ciccone and Jarocinski, 2010; Liang et al., 2008). In the following subsections, we present the prior framework and support our choices.

Parameter Priors

As noted previously, we use the Zellner's g prior structure, which is a common approach in the literature. It assumes that the priors on the constant and error variance from equation 2 are evenly distributed, $p(\alpha_i) \propto 1$ and $p(\sigma) \propto \sigma^{-1}$. Zeugner (2011) notes that this is very similar to the normal-gamma-conjugate model accounting for proper model priors on α and σ described, for example, in Koop (2003) with practically identical posterior statistics.

We assume that the β_i coefficients follow the normal distribution, and we have to formulate beliefs regarding their mean and variance before examining the data. Conventionally, researchers assume a conservative mean of 0 to reflect the lack of prior knowledge regarding the coefficients. Zellner's g defines their variance structure $\sigma^2(g(X_i'X_i)^{-1})$. Together, we have the coefficient distribution dependent on prior g:

$$\beta_i|g \sim \ N(0, \sigma^2(g(X_i'X_i)^{-1}) \tag{16}$$

The prior variance of the coefficients is proportional to the posterior variance $(X_i'X_i)^{-1}$ estimated from the sample. Parameter g denotes how much weight we attribute to the prior variance as opposed to the variance observed in the data (Feldkircher and Zeugner, 2009). Selecting a small g results in low variance in the prior coefficients and thus reduces the coefficients to zero. Conversely, a large g attributes higher importance to the data and expresses researchers' uncertainty regarding zero β_i coefficients (Zeugner, 2011). Note that with $g \to \infty$, $\beta_i \to \beta_i^{OLS}$. Popular choices include the following:

- Unit Information Prior (UIP); $g = N$.
- BRIC; $g = max\{N, K^2\}$.
- hyper-g; $\frac{g}{1+g} \sim Beta(1, \frac{a}{2} - 1)$, where $a \in (2, 4]$, which is a Beta distribution with mean $\frac{2}{a}$.

While the first two are known as "fixed-g" priors for the parameter prior set for all the models under consideration, hyper-g allows the researcher to update the prior for individual models in a Bayesian nature and therefore limits the unintended consequences of prior selection based on posterior results. Note that setting $a = 4$ corresponds to the UIP, whereas $a = 2$ concentrates the prior mass close to unity, corresponding to $g \to \infty$. For details on hyper-g, see Liang et al. (2008).

We employ the so–called hyper-g prior to estimate the baseline models, following Feldkircher and Zeugner (2009), who suggest that using model-specific priors leads to a more stable posterior structure. We then check the robustness of the results by applying the UIP parameter prior.

Model Priors

Moral-Benito (2012) notes that the most popular setting in the BMA literature is the binomial distribution, where each of the covariates is included in the model with a probability of success θ. The prior probability of model M_i with k_i regressors given θ is then

$$p(M_i) = \theta^{k_i}(1-\theta)^{K-k_i} \tag{17}$$

A standard setting is $\theta = \frac{1}{2}$, which assigns equal probability $p(M_i) = 2^{-K}$ to all the models under consideration. This model prior is also known as the uniform model prior. Assuming different values of θ can shift the prior model distribution to either smaller or larger sizes (see Zeugner (2011)).

We focus on models using the uniform model prior, which is typically employed in BMA applications Fernandez et al. (2001). However, the uniform model prior tends to assign greater weight to intermediate model sizes. In addition, the strong heredity principle suggested by Chipman (1996) has been used in the literature to assess the posterior inclusion probability of quadratic and interaction terms in the BMA framework. Following this convention, we rely on this principle whenever we consider quadratic or interaction terms in the analysis. It relates to the model prior probabilities in a sense that it essentially assigns zero model probability to the models violating preset conditions. In practice, the principle relies on MC^3 sampler, which ensures that whenever the square or interaction term is included in the model, the corresponding linear variables are included as well. Such algorithm ensures that the interaction or square term does not potentially mask any influence of the linear terms and therefore guarantees interpretation of the results.[5]

MCMC Sampler

One of the limitations of the BMA is its computational difficulty when the number of potential explanatory variables K is very large. Historically, this was the primary factor preventing researchers from employing Bayesian methods. Zeugner (2011) notes that for small models, it is possible to enumerate all variable combinations. When $K > 25$, it becomes impossible to evaluate the entire model space within a reasonable time frame. In such cases, BMA utilizes MC^3 samplers to approximate the crucial part of the posterior model distribution containing the most likely models. BMA applies the Metropolis-Hastings algorithm, which is outlined in Zeugner (2011), in following way:

At any step i, the sampler is currently at model M_i, having PMP $p(M_i|y,X)$. In the next step $i+1$, model M_j is proposed to replace M_i. The sampler accepts the new model M_j with the following probability:

$$p_{i,j} = min\left(1, \frac{p(M_j|y,X)}{p(M_i|y,X)}\right) \tag{18}$$

If model M_j is rejected, the next model M_k is suggested and compared with M_i. With the growing number of iterations, the number of times each model is retained converges to the distribution of posterior model probabilities. Typically, one of the following MC^3 samplers is used to draw the models:

- Birth-death sampler - randomly chooses one of the explanatory variables, which is included if it is not already part of the current model M_i or dropped if it is already in M_i.
- Reversible-jump sampler - with 50% probability, the Birth-death sampler is used to determine the next candidate model. With 50% probability, the sampler randomly swaps one of the covariates in M_i for a covariate previously excluded from M_i.

Because the sampler can begin with a "poor" model with low PMP, the predefined number of initial draws, the so-called burn-ins, are usually dropped. The quality of the approximation can be evaluated on the basis of the correlation between the PMP derived from an analytical approach and those obtained from the MC^3 sampler. It depends on the number of iterations (draws) and the likelihood of the initially selected model. Zeugner (2011) notes that a PMP correlation of approximately 0.9 indicates a "good degree of convergence". In the event that the correlation is lower, the number of sampler iterations should be increased.

[5] The appendix in Cuaresma et al. (2014) illustrates the mechanism in detail.

4 Results

Figure 1 and figure 2 offer an initial insight on the relationship between selected regressors and financial variables, respectively. The scatter plots dominantly suggest expected correlations. Figure 2 then illustrates the scatter plots where we relate wealth Gini coefficient to a selection of our financial variables. Access to financial services, represented by the number of bank branches per 100,000 inhabitants, is negatively correlated with inequality while depth of the financial markets, proxied by stock market capitalization as a share of Gross Domestic Product (GDP), is higher in countries with higher wealth inequality. Loan-to-deposit ratio and outstanding private credit do not show any significant dependency.

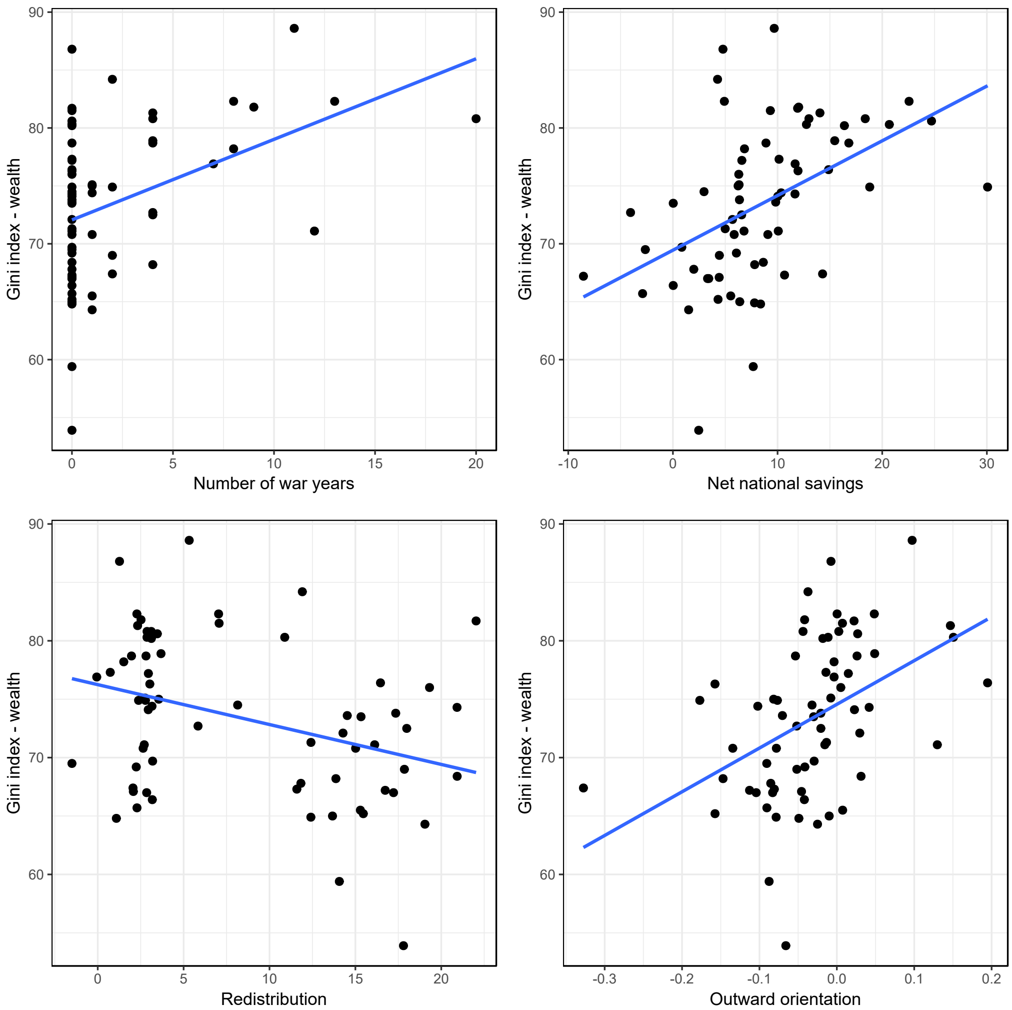

Figure 1: Wealth inequality and selected explanatory variables

Table 3 show the results of our baseline scenario. We present the explanatory variables sorted by their PIPs. Net national savings, number of war years, access to financial services, outward orientation, redistribution, and net foreign direct investment show up in the set of the most relevant regressors with PIPs above 0.6. In other words, they are part of the model explaining wealth inequality with a probability higher than 60%. The cut-off point for relevant variables is somewhat arbitrary, but if we considered slightly lower values around 50%, we would also include technological progress, gross fixed capital formation in the model, and credit to private sector.

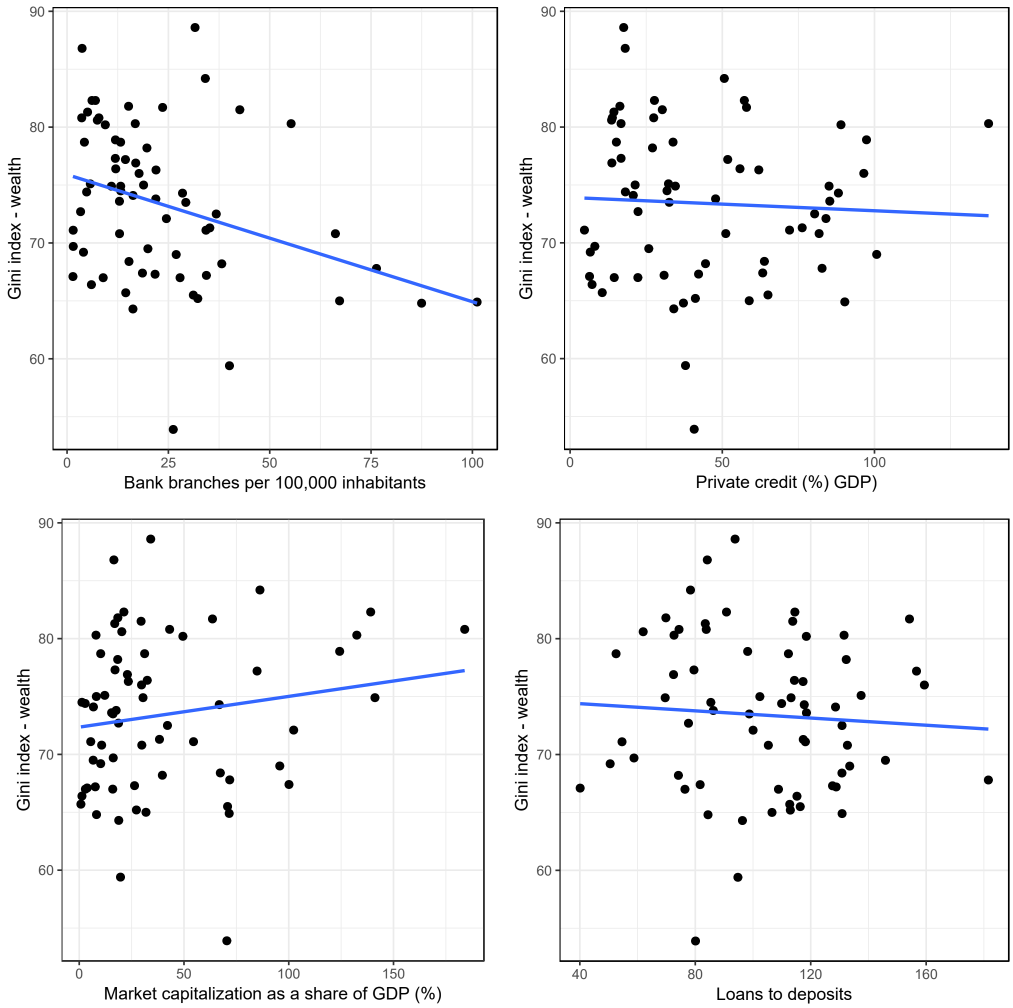

Figure 2: Wealth inequality and selected financial indicators

The variables with high PIPs show expected qualitative effects on wealth distribution. National savings along with number of war year increase wealth inequality within the country. It is interesting that the more country accumulates wealth, the more unequal is its distribution within the society. On the other hand, access to the financial markets leads to more uniform distribution of wealth. This is partially in line with conclusion by Claessens and Perotti (2007) who assert that access to financial resources is the key driver in reducing inequality rather than the depth of the market. This corresponds to lower inclusion probability of credit to private sector in our model. Interestingly, the sheer volume of credit actually implies higher levels of wealth inequality. Outward orientation capturing the openness of the economy leads to higher levels of wealth inequality. Large importance and qualitative effect corresponds to the earlier findings, such as Dabla-Norris et al. (2015), that claim globalization and increasing exposure to outside world endorses inequality. The authors also mention technological progress and implied increase in the skill premium encourage economic disparities. Redistribution, which we defined as the difference between market and after-tax income Gini indices also exhibits anticipated effect. With higher redistribution of income comes a lower inequality in terms of wealth. We understand the effect of net Foreign Direct Investment (FDI) through the lens of better economic opportunities and resulting lower levels of inequality.

We find wars to be associated with higher wealth inequality. This is at odds with previous evidence arguing that wars reduce inequality because of enormous capital destruction, inflation and large redistributive government programs (to finance the war), see, for example, (Piketty, 2014; Milanovic, 2016) and references therein. However, this evidence focuses on the effect of war on inequality over time and focuses on large and long-lasting conflicts such as World War I or II. Our regressions explain cross-sectional variation in inequality, i.e. why inequality is higher in some countries than in others. In addition, our dataset on wars is based on period after World War II, i.e. typically internal conflicts (civil wars) or conflicts involving a single or small number of countries. These conflicts have adverse macroeconomic effects, undermine rule of law, cause violent confiscation of private property by militia and reduce trust in society, especially if these conflicts occur repeatedly (Bircan et al., 2017). Bircan et al. (2017) study the effect of internal violent conflicts on income inequality and also find the inequality increases but this effect is temporary and later on, inequality falls slowly back to the steady state.

Table 3: Dependent variable - average Gini index (wealth) 2010-2016, 67 observations, baseline (hyper-g paremeter prior)

	PIP	Post Mean	Post SD
Net national savings	0.94	0.25505	0.13594
Number of war years	0.92	0.33569	0.19760
Bank branches/1000 inh.	0.89	-0.06142	0.03981
Outward orientation	0.88	19.70040	11.34045
Redistribution	0.87	-0.24221	0.16034
Net foreign direct investment	0.63	-0.26346	0.29446
Technological progress	0.50	1.77390	2.33089
Gross fixed capital formation	0.50	-0.18801	0.25329
Private credit	0.48	0.02395	0.03338
Inflation	0.47	0.00293	0.00433
Latin America dummy	0.26	0.60199	1.41519
Size of labour force	0.21	0.02134	0.05778
Value added in industry	0.21	0.03613	0.09550
Average GDP growth	0.20	-12.67465	36.74427
Population growth	0.18	-0.18242	0.58182
Market capitalization	0.17	0.00313	0.01137
Life expectancy	0.17	0.02496	0.08402
Rule of law	0.16	0.13277	0.47697
Banking diversification	0.16	-0.19229	0.69130
Leftwing orientation	0.15	-0.01003	0.03765
Education index (UN)	0.14	-1.05323	4.92983
Ethnolinguistic fractionalization	0.14	-0.29796	1.37795
Net interest margin	0.13	-0.03986	0.17967
Loan-to-deposits	0.13	0.00288	0.01208
Business conditions	0.12	-0.19405	0.91651
Labour market regulation	0.11	0.10747	0.53023
Market turnover	0.10	0.00117	0.00571
Bank Z-score	0.09	0.00330	0.03086
Civ. liberties and Pol. rights	0.09	-0.01304	0.24291
Public education expenditures	0.08	-0.01425	0.10940
Active banking restrictions	0.07	-0.01528	0.14106
Natural resources rents	0.07	0.00011	0.04738
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Government expenditures	0.07	0.00435	0.05983
Financial openness (Chinn-Ito)	0.06	-0.01003	0.16577
Population density	0.06	-0.00001	0.00036
Revolutions and coups	0.05	0.00142	0.03786

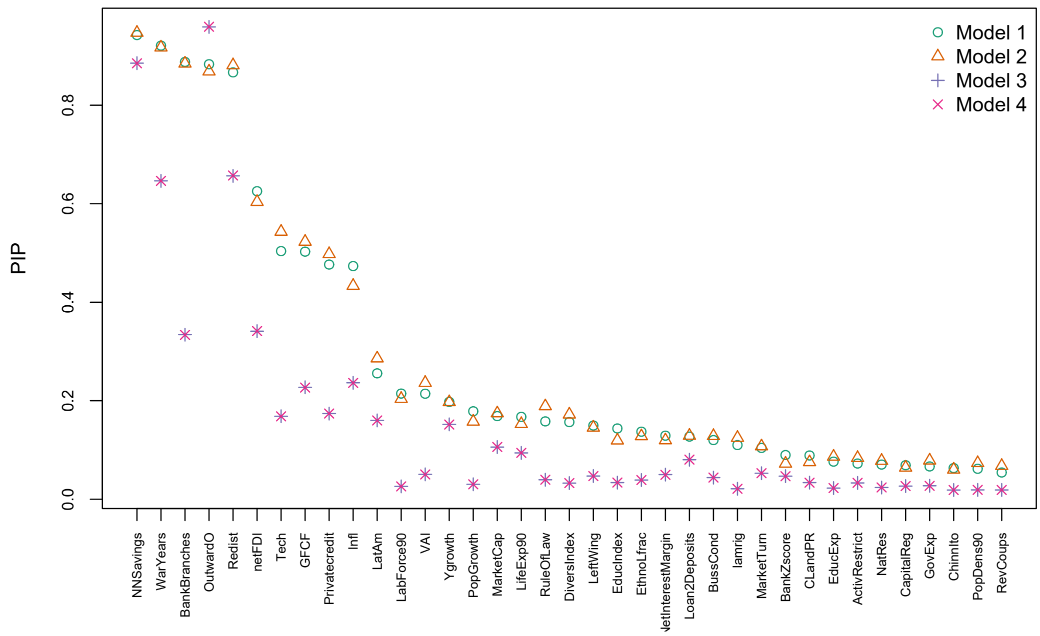

Figure 3: Parameter priors and MC3 sampler comparison. Model 1: hyper-g, birth-death; Model 2: hyper-g, reverse jump; Model 3: UIP, birth-death; Model 4: UIP, reverse jump

We report the baseline results where we employ uniform model prior and hyper-g parameter prior as described in section 3. We also rely on the birth-death MC^3 sampler in the process of approximation of the posterior model space. However, to provide some robustness checks we also try alternative parameter priors and samplers. Figure 3 present a graphical illustration of the robustness checks. We ran alternative specifications of the model using UIP and reverse-jump MC^3 sampler in all possible combinations. The additional estimations give confidence to our results. Optional sampler has only marginal effect on the output. Selection of a different parameter prior has a larger impact with general decrease in inclusion probabilities as smaller models are now suggested in the estimation, but the ordering of the variables among the most important ones remains quite stable along with the qualitative effects they indicate. We also tried other specifications with quadratic terms of financial variables, interactions between rule of law and financial variables, and others. None of these additional regressors had significant relevance in our model[6].

[6]These additional estimation results are available upon request.

5 Concluding Remarks

In this paper, we fill the gap in the literature on economic inequality by examining the determinants of wealth inequality. To this date we are not ware of any study which would address this topic. We use the wealth Gini index from yearly CSWD in the BMA framework to account for model uncertainty, given the underdeveloped theoretical background in the wealth inequality literature. In addition, we bring special focus on financial development among the explanatory variables and we include variables capturing diverse characteristics of financial systems. This helps us to properly account for the functions given to finance in theory.

Using a global sample of 67 countries, we identify several key variables driving wealth inequality. In different specifications within the BMA framework, redistribution and access to financial markets show decreasing effect on wealth inequality. The inflows of foreign direct investment also show tendencies to equalize wealth distribution. On the other hand, we find that national savings, number of war years, outward orientation, and technological progress all increase wealth inequality. Our conclusions are robust to the choice of different parameter priors and Monte Carlo samplers.

The effects of income redistribution and wars seem intuitive. Other estimated effects fit into the framework of thinking about inequality. Globalization, approximated in our sample by economic openness, along with technological progress have been identified as drivers of growing inequalities. Another result which stands out is the complex effect financial markets have on wealth inequality. On the one hand, access to banking seems to matter and decrease inequality. At the same time higher volume of outstanding credit to private sector promotes wealth inequality. These conclusions have important implications for policy and suggest that promoting access to finance could slow down or even reverse the trend of increasing inequality.

References

Alvaredo, F., A. B. Atkinson, T. Piketty, and E. Saez (2013). The top 1 percent in international and historical perspective. *The Journal of Economic Perspectives 27*(3), 3–20.

Anand, S. and P. Segal (2017). Who are the global top 1 *World Development 95*(Supplement C), 111 – 126.

Bircan, C., T. Bruck, and M. Vothknecht (2017). Violent conflict and inequality. *Oxford Development Studies 45*(2), 125–144.

Blume, L. E. and S. N. Durlauf (2015). Capital in the twenty-first century: a review essay. *Journal of Political Economy 123*(4), 749–777.

Chipman, H. (1996). Bayesian variable selection with related predictors. *Canadian Journal of Statistics 24*, 17–36.

Ciccone, A. and M. Jarocinski (2010). Determinants of economic growth: Will data tell? *American Economic Journal: Macroeconomics 2*(4), 222–246.

Cihak, M., A. Demirguc-Kunt, E. Feyen, and R. Levine (2013). Financial development in 205 economies, 1960 to 2010. Working Paper 18946, NBER.

Claessens, S. and E. Perotti (2007). Finance and inequality: Channels and evidence. *Journal of comparative Economics 35*(4), 748–773.

Cuaresma, J. C., G. Doppelhofer, and M. Feldkircher (2014). The determinants of economics growth in european regions. *Regional Studies 48*, 44–67.

Dabla-Norris, E., K. Kochhar, N. Suphaphiphat, F. Ricka, and E. Tsounta (2015). *Causes and consequences of income inequality: a global perspective.* International Monetary Fund.

Davies, J. B., R. Lluberas, and A. F. Shorrocks (2016). Estimating the level and distribution of global wealth, 2000-14. Technical report, WIDER Working Paper.

Davies, J. B., S. Sandström, A. Shorrocks, and E. N. Wolff (2011). The level and distribution of global household wealth. *The Economic Journal 121*(551), 223–254.

de Haan, J. and J.-E. Sturm (2017). Finance and income inequality: A review and new evidence. *European Journal of Political Economy*.

Durlauf, S. N., A. Kourtellos, and C. M. Tan (2008). Are any growth theories robust? *The Economic Journal 118*, 329–346.

Feldkircher, M. and S. Zeugner (2009). Benchmark priors revisited: On adaptive shrinkage and the supermodel effect in bayesian model averaging. Working Paper 09/202, Internation Monetary Fund.

Fella, G. and M. De Nardi (2017). Saving and wealth inequality. *Review of Economic Dynamics*.

Fernandez, C., E. Ley, and M. F. Steel (2001). Model uncertainty in cross-country growth regressions. *Journal of Applied Econometrics 16*(5), 563–576.

Hasan, I., R. Horvath, and J. Mares (2018). What type of finance matters for growth? bayesian model averaging evidence. *World Bank Economic Review*, forthcoming.

King, J. E. (2017). The literature on piketty. *Review of Political Economy 29*(1), 1–17.

Koop, G. (2003). *Bayesian Econometrics.* Wiley.

Koop, G., D. J. Poirier, and J. L. Tobias (2007). *Bayesian Econometric Methods.* Cambridge University Press.

Liang, F., R. Paulo, G. Molina, M. A. Clyde, and J. O. Berger (2008). Mixtures of g priors for bayesian variable selection. *Journal of the American Statistical Association 103*(481), 410–423.

Mankiw, N. G. (2015). Yes, r¿ g. so what? *The American Economic Review 105*(5), 43–47.

Milanovic, B. (2016). *Global inequality.* Cambridge: Harvard University Press.

Moral-Benito, E. (2012). Determinants of economic growth: A bayesian panel data approach. *The Review of Economics and Statistics 94*(2), 566–579.

Pástor, L. and P. Veronesi (2016). Income inequality and asset prices under redistributive taxation. *Journal of Monetary Economics 81*, 1–20.

Piketty, T. (2014). *Capital in the twenty-first century.* Cambridge: Harvard University Press.

Piketty, T. and G. Zucman (2014). Capital is back: Wealth-income ratios in rich countries 1700–2010. *The Quarterly Journal of Economics 129*(3), 1255–1310.

Raftery, A. E., D. Madigan, and J. A. Hoeting (1997). Bayesian model averaging for linear regression models. *Journal of the American Statistical Association 92*(437), 179–191.

Rowthorn, R. (2014). A note on piketty's capital in the twenty-first century. *Cambridge Journal of Economics 38*(5), 1275–1284.

Saez, E. and G. Zucman (2016). Wealth inequality in the united states since 1913: Evidence from capitalized income tax data. *The Quarterly Journal of Economics 131*(2), 519–578.

Soskice, D. (2014). Capital in the twenty-first century: a critique. *The British journal of sociology 65*(4), 650–666.

Zeugner, S. (2011). *Bayesian Model Averaging with BMS.*

A Appendix

A.1 Additional robustness checks

Table 4: Dependent variable - average Gini index (wealth) 2010-2016, 67 observations, UIP parameter prior

	PIP	Post Mean	Post SD
Net national savings	0.94	0.25505	0.13594
Number of war years	0.92	0.33569	0.19760
Bank branches/1000 inh.	0.89	-0.06142	0.03981
Outward orientation	0.88	19.70040	11.34045
Redistribution	0.87	-0.24221	0.16034
Net foreign direct investment	0.63	-0.26346	0.29446
Technological progress	0.50	1.77390	2.33089
Gross fixed capital formation	0.50	-0.18801	0.25329
Private credit	0.48	0.02395	0.03338
Inflation	0.47	0.00293	0.00433
Latin America dummy	0.26	0.60199	1.41519
Size of labour force	0.21	0.02134	0.05778
Value added in industry	0.21	0.03613	0.09550
Average GDP growth	0.20	-12.67465	36.74427
Population growth	0.18	-0.18242	0.58182
Market capitalization	0.17	0.00313	0.01137
Life expectancy	0.17	0.02496	0.08402
Rule of law	0.16	0.13277	0.47697
Banking diversification	0.16	-0.19229	0.69130
Leftwing orientation	0.15	-0.01003	0.03765
Education index (UN)	0.14	-1.05323	4.92983
Ethnolinguistic fractionalization	0.14	-0.29796	1.37795
Net interest margin	0.13	-0.03986	0.17967
Loan-to-deposits	0.13	0.00288	0.01208
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Labour market regulation	0.11	0.10747	0.53023
Market turnover	0.10	0.00117	0.00571
Bank Z-score	0.09	0.00330	0.03086
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Public education expenditures	0.08	-0.01425	0.10940
Active banking restrictions	0.07	-0.01528	0.14106
Natural resources rents	0.07	0.00011	0.04738
Bank capital regulations	0.07	-0.01269	0.11135
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Population density	0.06	-0.00001	0.00036
Revolutions and coups	0.05	0.00142	0.03786

A.2 Dataset description

Table 5: List of variables

Variable	Definition (+ optional comments)	Source
GiniWealth	Gini index based on the distribution of wealth from Credit Suisse Wealth Reports 2010-2016	Credit Suisse
NatRes	Total natural resources rents are the sum of oil rents, natural gas rents, coal rents (hard and soft), mineral rents, and forest rents. Average 1980-2009	WB
PopGrowth	Annual population growth 1980-2009	WB
GovExp	General government final consumption expenditure (formerly general government consumption). Average 1980-2009	WB
NNSavings	Net national savings (gross national savings less the value of consumption of fixed capital, % GNI). Average 1980-2009	WB
EducExp	Education expenditure refers to the current operating expenditures in education, including wages and salaries and excluding capital investments in buildings and equipment. Average 1980-2009.	WB
Infl	Inflation as measured by the consumer price index. Average 1980-2009.	WB
VAI	Industry value added (% GDP). Average 1980-2009.	WB
StartBussC	Cost of business start-up procedures (% of GNI per capita). Average 1980-2009	WB
StartBussT	Time required to start a business (days). Average 1980-2009	WB
GFCF	Gross fixed capital formation (% of GDP). Average 1980-2009	WB
NetFDI	Foreign direct investment, net inflows (% of GDP). Average 1980-2009	WB
Ygrowth	Annual growth of GDP. Average 1980-2009	PWT 9.0
LifeExp90	Life expectancy at birth in 1990	WB
LabForce90	Total labor force comprises people ages 15 and older who meet the International Labour Organization definition of the economically active population: all people who supply labor for the production of goods and services during a specified period. Labour force total, 1990. Not available before 1990.	WB
PopDens90	Population density (people per sq. km of land area) in 1990.	WB
RevCoups	Revolutions and coups, total instances between 1950 and 2010	Powell and Thyne (2011)
EthnoLfrac	Ethnolinguistic franctionalization. The most detailed/disaggregated fractionalization measure (ELF.15 in the original paper) is assumed as it is found most relevant to growth and has highest correlation with other fractionalization measure by Alesina et al. (2003)	Desmet et al. (2009)

WarYears	Number of war years (including civil wars) between 1946-2009 as defined in the UCDP dataset (more than 1000 casulties within a year)	UCDP/PRIO data
RuleOfLaw	Rule of law 1970-2009 (*alternatively WB has data 1996-2014*)	Fraser institute
CivLib	Civil liberties 1973-2009	Freedom House
PolRights	Political rights 1973-2009	Freedom House
OutwardO	Measure of outward orientation derived as Net exports/GDP (*previously based on data 1950-1983*)	PWT 9.0
LatAm	1 for Latin American countries	
ChinnIto	Chinn-Ito index of financial opennes. Average 1980-2010.	Chinn-Ito
LeftWing	Number of years between 1980 and 2009 when left oriented party lead the country.	DPI
ActivRestrict	Activity restrictions. Regulatory restrictions on bank activities and the mixing of banking and commerce.	Barth et al. (2013)
CapitalReg	Capital Regulatory index.	Barth et al. (2013)
DiversIndex	Whether there are explicit, verifiable, quantifiable guidelines for asset diversification and banks are allowed to make loans abroad.	Barth et al. (2013)
LAMRIG	Index capturing the rigidity of employment protection legislation	Laurent & Campos (2012)
Tech	Index on the level of technological development base on CHAT dataset	Comin & Hobijn (2009)
EducIndex	Calculated using mean years of schooling and expected years of schooling	UN
NetInterestMargin	Accounting value of banks' net interest revenue as a share of average interest-bearing assets; a measure of the efficiency of the banking sector.	GFDD
BankZScore	return on banks' assets plus the ratio of banks' equity and assets, divided by the standard deviation of the return on assets (ROA+equity/assets)/sd(ROA); a measure of stability of the banking sector	GFDD
Privatecredit	Domestic private credit to the real sector to GDP; a measure of the depth of the banking sector	GFDD
MarketCap	Value of listed shares to GDP; a measure of the depth of stock markets.	GFDD
MarketTurn	Stock market value traded to total market capitalization; a measure of the efficiency of stock markets.	GFDD
BankBranches	Number of bank branches per 100,000 adults	GFDD
Loan2Deposits	Loan-to-deposit ratio.	GFDD
Redist	Difference between market (pre-tax) and net (after-tax0 Gini index based on distribution of income (The Standardized World Income Inequality Database).	Solt (2016)