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Finance and Wealth Inequality

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Abstract

Using a global sample, this paper investigates the determinants of wealth inequality capturing various economic, financial, political, institutional, and geographical indicators. Using instrumental variable Bayesian model averaging, it reveals that only a handful of indicators robustly matter and finance plays a key role. It reports that while financial depth increases wealth inequality, efficiency and access to finance reduce inequality. In addition, redistribution and education are associated with lower inequality whereas wars and openness to international trade contribute to greater wealth inequality.

JEL-Classification: D31, E21

Keywords: Wealth inequality, finance, Bayesian model averaging

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1. Introduction

Wealth inequality differs markedly across countries (Davies et al., 2011, 2017; Milanovic, 2016). The wealth share of the top 1% in the US is currently approximately 40%, and it is even higher in Russia. On the other hand, the wealth share of the top 1% is approximately 20% in France and even lower in the UK (Zucman, 2018). What accounts for these (dramatic) differences in wealth inequality across countries? Is it different degrees of redistribution, financial development, globalization, technological progress or economic development? Alternatively, are there possibly some other factors? Although extensive progress has been made regarding the measurement of wealth inequality (Alvaredo et al., 2013; Davies et al., 2011, 2017; Piketty and Zucman, 2014; Saez and Zucman, 2016), we still lack systematic evidence about the determinants of wealth inequality across countries.

The theoretical models of wealth inequality suggest that several factors affect wealth inequality. The theoretical principles of the $r > g$ concept[1] laid out in Piketty (2014) predict that there is a natural tendency of wealth inequality to increase in capitalist economies, which can be overcome only by redistribution or wars. This concept has received criticism from the theoretical point of view (Blume and Durlauf, 2015; Mankiw, 2015).[2]

Dynamic quantitative models represent another approach to understand wealth inequality and focus on the heterogeneity of returns, preferences, transmission of human capital, and bequests. Nardi and Fella (2017) provide an overview of these models and their ability to mirror empirical wealth distributions. One of the conclusions is that all of the models critically rely on the saving motives of individuals. The theoretical predictions regarding wealth inequality arise from the model by Pástor and Veronesi (2016), in which inequality depends on the skill and risk aversion of entrepreneurs, taxation, and the development of financial markets.[3] Overall, the theoretical models postulate that several factors may matter for wealth inequality but do not provide a single theoretical framework to guide the exact regression model specifications.

[1] This means that the rate of return on capital, r, exceeds economic growth, g.

[2] See King (2017) for a review of the literature about the topic.

[3] More specifically, it depends on the ability of entrepreneurs to diversify away their idiosyncratic risk, whichcan be interpreted as a measure of financial development.

In this paper, we study the potential determinants of wealth distribution by relying on a global sample of countries and examining a wide array of possible determinants. Given that there is no encompassing theoretical framework, we propose to employ Bayesian Model Averaging (BMA) as our methodological framework. BMA is a well-established approach within statistical theory and addresses the inherent regression model uncertainty in a unifying framework (Koop et al., 2007; Raftery et al., 1997).[4]

In essence, the 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 the evaluation of numerous regressors and estimating their Posterior Inclusion Probability (PIP), the probability that a given regressor should be in the 'optimal' model of wealth inequality. We address potential endogeneity within the estimation by using lagged values of explanatory variables and, more rigorously, by relying on the Instrumental Variable Bayesian Model Averaging (IVBMA) approach by Karl and Lenkoski (2012).

Using our BMA approach, we examine how 37 different factors explain the differences in cross-country wealth inequality among 73 countries. We focus on a number of economic, financial, institutional, regulatory, political and policy factors, such as education, financial development, government policies, technological progress, entrepreneurship and macroeconomic stability. To capture wealth inequality, we use the wealth Gini coefficient from Credit Suisse Wealth Databook (CSWD), constructed using the methodology of Davies et al. (2017). The CSWD is the only available dataset with sufficient country coverage. We also add a set of indicators for financial development by Svirydzenka (2016), which employ the most densely available series from Global Financial Development Database (GFDD) to capture various characteristics of financial systems. We include these measures to reflect the assumptions made by the theory, in which savings, which depend on financial markets, and financial development are the main drivers of wealth inequality.

[4] BMA has been appliedto examine various issues in economics and finance, such as to study economic growth (Durlauf et al., 2008; Fernandez et al., 2001), stock market predictability (Avramov, 2002; Cremers, 2002), intertemporal elasticity of substitution (Havranek et al., 2015), exchange rate forecasting (Wright, 2008) and interactions between credit spreads and economic activity (Faust et al., 2013).

Examining our global sample, we find that several factors are robustly related to wealth inequality. We find that financial development is an especially important determinant of wealth inequality across countries. Our results suggest that finance exerts a complex effect on wealth inequality. Whereas countries with more finance (i.e., large financial markets and financial institutions) exhibit greater wealth inequality, more efficiency and greater access to finance is associated with less wealth inequality. In general, this evidence supports the notion that sound financial systems contribute to lower wealth inequality. According to our results, the empirical importance of finance for wealth inequality suggests that theoretical models should more thoroughly examine the complex links between finance and wealth.

Our results also suggest that education reduces wealth inequality. Education decreases the gap between the wealthy and poor, corresponding to the findings by Dabla-Norris et al. (2015) regarding the determinants of income inequality.[5] Wealth inequality is also lower in countries with more redistribution, as measured by the difference between the market and after-tax income Gini coefficients. Finally, globalization, as proxied by trade openness, and the extreme form of political instability, as proxied by the number of wars, tend to increase wealth inequality.

The remainder of the paper is organized as follows. Section 2 reviews the literature on wealth inequality. Section 3 presents the data, and 4 introduces the BMA. We provide the results in section 5 and conclude in section 6. Additional robustness checks are available in the Appendix A.

[5] However, note that the theoretical effect of education on inequality is ambiguous. Scheidel (2017) discusses the channels via which education – primarily through assortative mating and the elite school system being disproportionally less accessible to children from poor families – amplifies inequality.

2. Related literature

Wealth inequality is typically analyzed within the theoretical framework of Bewley (1977) and Aiyagari (1994). This framework relaxes the assumption of efficient economies and allows for, among other aspects, incomplete markets. The agents within the economy face a stochastic process of labor earnings and optimize consumption-saving behavior in incomplete markets. Additional specifications include restrictions on saving assets or borrowing constraints. Among other macroeconomic phenomena, the models can help US to understand the dynamics of the equilibrium distributions of consumption, savings, and wealth (Benhabib et al., 2015).

The basic mechanism in the Bewley model relies on the environment in which agents save to self-insure against idiosyncratic labor-earning shocks. This precautionary motive to save is the primary driver of wealth accumulation. The basic version of the model has severe limitations. The ability to self-insure increases with the wealth/earnings ratio. The saving rate thus decreases and eventually turns negative if individual wealth is sufficiently greater than labor earnings. In other words, the basic setup implies negative saving rates for the rich. It also overstates the fraction of the population that does not save at all. These features of the model are in contrast with the data in United States (US), in which we observe high saving rates for the rich, and the share of agents without savings is very small (Nardi and Fella, 2017).

For this reason, the saving motives are extended to account more accurately for the actual dynamics of wealth accumulation and distribution. Some of the extensions introduce bequests and the transmission of human capital across generations (De Nardi, 2004; De Nardi and Yang, 2014), heterogeneity in both time preferences and risk aversion (Hendricks, 2007), earnings risk (Castañeda et al., 2003), saving for out-of-pocket medical expenses (Kopecky and Koreshkova, 2014), heterogeneity in rates of return (Lusardi et al., 2017; Benhabib et al., 2015), or entrepreneurship motives for saving (Cagetti and De Nardi, 2006). The extensions generally help the model fit actual data. The various forces that we mention above have been primarily studied separately, which makes it difficult to evaluate their relative importance. Therefore, Nardi and Fella (2017) call for complex models that account jointly for varying saving motives.

Empirical analysis of wealth inequality has received much less attention compared with income. Even though this may seem surprising given the quantitative importance of wealth, it is largely because the measurement of wealth is more complicated than the measurement of income (Zucman, 2018).

Private wealth is of utmost importance for individual decisions regarding investment, especially in an environment with asymmetric information and binding credit constraints. The consequences of the distribution of wealth are important in theories explaining the different speeds of development across countries (Roine and Waldenström, 2015). Researchers sometimes substitute wealth patterns with income distributions, but such replacements are far from perfect given that wealth and income distributions are typically very different (Bagchi and Svejnar, 2015). One of the stylized facts is that the wealth distribution is much more concentrated than the income distribution. Figure A1 in the Appendix illustrates this difference for the OECD countries with the most unequally distributed income. We can also observe countries with relatively high income inequality and low wealth inequality, and *vice versa*.

The lack of empirical literature regarding wealth inequality is primarily caused by data limitations, although some recent attempts to map both historical and current wealth patterns have emerged. The main sources of wealth data include household surveys, wealth tax returns, estate tax returns, the investment income method (jointly examining capital income and the net rate of return), and the *rich lists* assembled by various journals (Davies and Shorrocks, 2000).

In their survey, Roine and Waldenström (2015) combine different sources of data and provide a long-run perspective on wealth inequality in advanced economies for which data are available[6] The data for these countries are typically available for the 20th century (and sometimes even earlier) but often at a frequency lower than yearly and with some missing data. Typically, the data indicate that wealth inequality has decreased since World War I, continued on a downward trend (or stagnated) and then increased somewhat since the 1980s. However, the increase in wealth inequality after the 1980s is most dramatic for some countries, such as the US, where it nearly reverted the top wealth shares to their values from before the Great Depression (Piketty, 2014).

The existing single case studies of countries include, among others, Saez and Zucman (2016) and Kopczuk and Saez (2004), who document the dynamics of wealth inequality in the US since 1913 based on capitalized income data and estate tax returns, respectively. Dell et al.

[6] Australia, Denmark, Finland, France, Netherlands, Norway, Sweden, Switzerland, United Kingdom (UK), and the US.

(2007) examine the evolution of wealth shares in Switzerland. Roine and Waldenström (2009) document the Swedish case, and Katic and Leigh (2016) cover the wealth patterns in Australia. For a thorough overview, we refer to Roine and Waldenström (2015).

Davies et al. (2017, 2011); Davies and Shorrocks (2000) are important contributions in terms of measuring wealth inequality. In order to examine global wealth inequality, they provide wealth inequality measures (Gini coefficients) for a large number of countries. They explore a shorter time span, only examining the changes in global wealth patterns since 2000, and find that global wealth inequality decreased between 2000 and 2007, but then the trend reversed, and inequality has since been steadily rising. They also show that the share of financial assets strongly affects the changes in wealth inequality (Davies et al., 2017). We provide more details of their work, especially regarding the wealth inequality levels in individual countries, in the section about data below.

3. Data

We construct a rich dataset of 73 countries and 37 explanatory variables to study the determinants of the wealth distribution. The selection is based on the aforementioned theoretical models and the empirical studies examining income inequality. Our methodological choice allows US to be generous with the inclusion of regressors, and therefore, we can capture a variety of different country characteristics.

Our dependent variable is the Gini index based on the wealth distribution coming from the CSWD based on the methodology of Davies et al. (2011, 2017).[7] They use the methodology to estimate the world distribution of wealth and consequently provide estimates for single countries. The CSWD is provided at a yearly frequency from 2010 onwards. We take the average of available observations of the index (2010–2016) to reduce possible year-on-year stock market capitalization swings or significant changes in the valuation of nonfinancial assets. We describe this dataset more thoroughly in subsection 3.1.

We supplement the data about wealth with a large number of potential variables that could be driving inequality. These cover economic, financial, institutional, political, social and cultural aspects of the countries in our sample. We then average the data over the period of their availability, which is typically from 1980 to 2009. The complete list of the explanatory variables along with their description and sources is available in the Appendix.

We focus on financial development and its effect on the distribution of wealth within the economy. There are more than 100 indicators available in GFDD by the World Bank (WB), capturing specific features of financial development. Building on the framework by Cihak et al. (2013), who describe four main dimensions of financial systems – depth, efficiency, stability, and access – Svirydzenka (2016) constructs aggregate indexes representing these dimensions using the most densely available series in the database. Furthermore, GFDD allows for not only distinguishing between the different dimensions of financial development but also ascribing these dimensions to the banking sector and financial markets separately. Except for stability and access, for which we only control for variables representing the banking industry due to data limitations, we take advantage of this distinction in our analysis.

[7] This dataset has been recently used by Anand and Segal (2017) to document recent trends in wealth inequality and by Islam (2018) to examine the effect of wealth inequality on economic freedom and democracy.

Table 1 lists the components of our financial indexes. Their construction follows standard procedures. The series are normalized and then aggregated into the index using a weighted linear average. The weights come from principle components analysis, and they are thus proportional to the relative importance of the underlying series in explaining the variance of the index. We limit the index data to a period for which at least one of the underlying series used for construction of the index is available.[8] We follow the same procedure as with other explanatory variables, i.e., take averages of the series before 2009.

Table 1: Underlying Components of Financial Development Indexes

INDICATOR	MEASURE
Financial institutions	
Access	Bank branches per 100,000 adults ATMs per 100,000 adults
Efficiency	Net interest margin Lending-deposits spread Noninterest income to total income Overhead costs to total assets Return on assets Return on equity
Depth	Domestic private credit to the real sector to the GDP Pension fund assets/GDP Mutual fund assets/GDP Insurance premiums life and nonlife/GDP
Financial markets	
Depth	Stock market capitalization/GDP Stocks traded/GDP International debt securities of government/GDP Total debt securities of financial corporations/GDP Total debt securities of nonfinancial corporations/GDP
Efficiency	Stock market turnover ratio (stocks traded/capitalization)

[8] Originally, Svirydzenka (2016) imputes the value of the indices using other available data to provide complete time series for all of the indices since 1980. Due to missing data for some components in the early periods, they impute some of the indices. As an example, they approximate access to financial institutions by the series capturing efficiency or depth. In order not to mix up these concepts, we must impose conditions on the raw data availability.

Table 2: Finance and Wealth Inequality: Descriptive Statistics

	Min	Max	Mean	Std. dev
Wealth inequality	53.9	88.6	72.94	6.54
Access (FI)	0.015	0.964	0.336	0.259
Efficiency (FI)	0.280	0.765	0.584	0.123
Depth (FI)	0.022	0.861	0.306	0.239
Depth (FM)	0.004	0.732	0.220	0.203
Efficiency (FM)	0.012	0.953	0.348	0.260

Note: FI – financial institutions, FM - financial markets

Table 2 presents the descriptive statistics for the wealth inequality and financial development indicators, whereas Table 3 reports a correlation matrix for the financial variables and wealth inequality. It is important to realize that contrary to common perception, the correlations between financial variables are far from unity, with the only exception of access and depth, suggesting that different variables convey different information. Wealth inequality is correlated with financial variables, positively with depth and negatively with access and efficiency.

Table 3: Finance and Wealth Inequality: Correlations

Wealth inequality	1.00					
Access (FI)	–0.20	1.00				
Efficiency (FI)	–0.18	0.29	1.00			
Depth (FI)	0.08	0.73	0.48	1.00		
Depth (FM)	0.19	0.62	0.45	0.91	1.00	
Efficiency (FM)	0.02	0.47	0.12	0.51	0.58	1.00

Note: FI – financial institutions, FM – financial markets

3.1 CSWD

There are several sources for wealth data, with varying country and time coverage. World Inequality Database (WID) provides longer time series regarding wealth distribution for the us, Russia, the UK, and France. The coverage significantly improves[9] for aggregate stocks of wealth and wealth-income ratios, but these variables themselves do not provide information

[9] WID currently (2018) provides time series of varying length for 21 countries.

about the wealth distribution. The Organisation for Co-operation and Development (OECD) also systematically collects data regarding household wealth and its distribution since 2009. Information about the wealth share of the top decile and top percentile of the distribution is available for other metrics. However, the sample is constrained to the OECD member countries, and the resulting country-period sample does not allow for thorough analysis at the global level. Finally, the CSWD is a global yearly dataset regarding wealth and its distribution. In addition to the mean wealth levels for individual countries and different world regions, it provides data about the distribution in terms of Gini coefficients and top wealth shares.

The wealth distributions in the CSWD result from the methodology by Davies et al. (2017). The authors work with the definition of net worth — the sum of the marketable value of financial and nonfinancial assets (housing and land), from which debts are subtracted. Financial assets include private pensions, but this quantity does not consider entitlements for public pensions. Whereas there is uncertainty related to future pension payments, Bönke et al. (2017) document that under no policy change, wealth inequalities decrease if they account for private, occupational, and public pensions. The CSWD focuses on the wealth of individuals aged 20+ years. Several arguments for addressing individuals rather than households exist. First, personal assets and liabilities are usually attached to individuals, and their commitment does not depend on household membership. Second, even when some assets are shared, household members neither have equal roles in management of these assets nor benefit from their eventual sale. Third, the *de facto* composition of the household might not correspond to the survey questionnaires; older children might live away from home, which also relates to the different household structures across countries. Finally, in contrast with the number of adults, the exact number of households in many countries is unknown. Generally, the implications of this choice of unit of comparison are uncertain. Although household wealth appears to be distributed more equally than that of individuals Atkinson and Piketty (2007), some contributions show there are no important differences in Sweden and the US (Roine and Waldenström, 2009; Kopczuk and Saez, 2004).

The construction of wealth distributions in the CSWD follows three steps. Initially, the average level of wealth is established for individual countries. Household Balance Sheet (HBS) data are the primary source for wealth levels.[10] The second step addresses the wealth pattern within countries. Based on the wealth distribution in countries for which the data are directly available (31 countries), Davies et al. (2017) establish a relationships between wealth and income distribution to provide an estimate of the wealth pattern in the remaining countries for which they observe the distribution of income. Finally, they augment the resulting wealth distribution by using the lists of billionaires by Forbes. The common sources of wealth distribution likely underestimate the wealth holdings of the very rich, and this results in a distorted top-tail of wealth spectrum. Therefore, CSWD employs Forbes data to adjust the top-tail of the distribution.

[10] HBS data are available for 47 countries. For many countries, data regarding nonfinancial wealth are missing, and thus, the basic data must be supplemented by econometric estimations. For more details about the estimated regressions for financial assets, nonfinancial assets, and liabilities, we refer to Davies et al. (2017).

4. Bayesian Model Averaging

We describe BMA in this section. One of major benefits of BMA is the possibility to deal with the regression model uncertainty. This uncertainty arises in cases of competing theories, which suggest different regression specifications. In addition, Koop (2003) warns about risks related to general-to-specific modeling, i.e., starting with a more general regression model and narrowing down the specification by sequentially dropping the least significant regressors in order to obtain the "true" model. Koop (2003) shows that the risk of arriving at a model different from "true" 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 rather averages all possible regression models, assigning greater weight to "better" models based on their likelihood. Therefore, the BMA addresses the regression model uncertainty inherent in many economic theories.

We provide a detailed description of standard BMA model in the Appendix A. In what follows, we present the reasoning for the choices of our parameter and model priors as well as the reasoning how we adress potential endogeneity concerns.

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 structure and support our choices.

Parameter Priors

We use Zellner's g prior structure, which is a common approach in the literature. The prior structure assumes that the priors on the constant and error variance from equation A2 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 must formulate beliefs regarding their mean and variance before examining the data. We follow standard practice and 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, which depends on the prior g:

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

The prior variance of the coefficients is proportional to the posterior variance $(X_i{}'X_i)^{-1}$ estimated from the sample. The 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 pushes 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 Unit Information Prior (UIP), BRIC[11], and hyper-g[12] parameter prior. Whereas 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 more details about 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) states 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 withk_i regressors given θ is then

$$p(M_i) = \theta^{k_i}(1-\theta)^{K-k_i} \quad (2)$$

[11] $g = \max N, K^2$

[12] $\frac{g}{1+g} \sim Beta(1, \frac{a}{2} - 1)$, where $a \in (2,4]$, i.e. Beta distribution with mean $\frac{2}{a}$

A standard setting is $\theta = \frac{1}{2}$, which assigns equal probability $p(M_i) = 2^{-K}$ to all of the models under consideration. This model prior is also known as the uniform model prior. Assuming that 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).

A few other model priors can be found in the literature, and we also use them for sensitivity checks of our results. In particular, we employ the collinearity-adjusted dilution model prior described by George (2010). Whereas the uniform model prior assumes that the probability of inclusion of one regressor is independent of the inclusion of another one, some regressors are usually correlated. A simple method for addressing the dilution property is to account for such collinearity and adjust the model probabilities by weighting them with the determinant of the correlation matrix, $|R_i| = |X_i X_i'|$. In practice, the collinearity-adjusted dilution model prior takes the following form:

$$p(M_i) = |R_i| \theta^{k_i} (1-\theta)^{K-k_i} \tag{3}$$

where R_i is the correlation matrix of model i under consideration. If the variables in the examined model are orthogonal, the determinant $|R_i|$ goes to 1. On the other hand, if the variables are highly collinear, it goes to 0 and consequently down-weights models with redundant regressors.

IVBMA

Karl and Lenkoski (2012) present an approach to address model uncertainty in the instrumental variable framework. In their paper, they use Conditional Bayes Factors (CBFs) factors to compare models within the Gibbs sampling algorithm to efficiently compute the posteriors. In contrast with Lenkoski et al. (2014), who rely on approximation of model probabilities using Bayesian Information Criterion (BIC), IVBMA allows for a rigorous and fully Bayesian approach. The solution by Koop et al. (2012) offers an alternative approach to simultaneously account for endogeneity and model uncertainty. Their method allows for more flexibility in the choice of prior distributions, and it is suitable for testing the identification of the estimated system. This flexibility complicates the estimation process by introducing an extremely large model space and complexity of the algorithm, which may manifest as difficulties in mixing. The authors are forced to introduce a tweak using a system of "hot", "cold", and "super-hot" models to improve on the mixing properties, which makes the method much more difficult to implement.

We follow Karl and Lenkoski (2012) in the concise exposition of the IVBMA framework. They start from a classical two-stage model:

$$Y = X\beta + W\gamma + \epsilon \tag{4}$$

$$X = Z\delta + W\tau + \eta \tag{5}$$

where

$$\begin{pmatrix} \epsilon_i \\ \eta_i \end{pmatrix} \sim \mathcal{N}_2(0, \Sigma) \tag{6}$$

and

$$\Sigma = \begin{pmatrix} \sigma_{11} & \sigma_{12} \\ \sigma_{21} & \sigma_{22} \end{pmatrix}; \sigma_{12} = \sigma_{21} \neq 0 \tag{7}$$

In this system of equations, Y is the response variable, X is the endogenous factor, and W represents a matrix of other explanatory variables. Z is a matrix of instrumental variables, whereas δ, γ and τ are the corresponding parameter matrices, and β is a scalar. For ease of exposition of the model, we include only one endogenous variable, but extension to multiple endogenous variables can be readily performed.

The IVBMA algorithm works by sequentially updating the first- and second-stage models by drawing from their respective neighborhood models and comparing the conditional probabilities of the candidate models. In a manner resembling the comparison of model probabilities within the MC3 sampler presented in Appendix A, the models are accepted and parameters updated if and only if the conditional probability of the suggested model is greater than the conditional probability of the current one. The error matrix Σ is updated after each round of considering new candidate models in both stages. For more details about the algorithm and algebraic exposition of CBFs, we refer to the original paper by Karl and Lenkoski (2012).

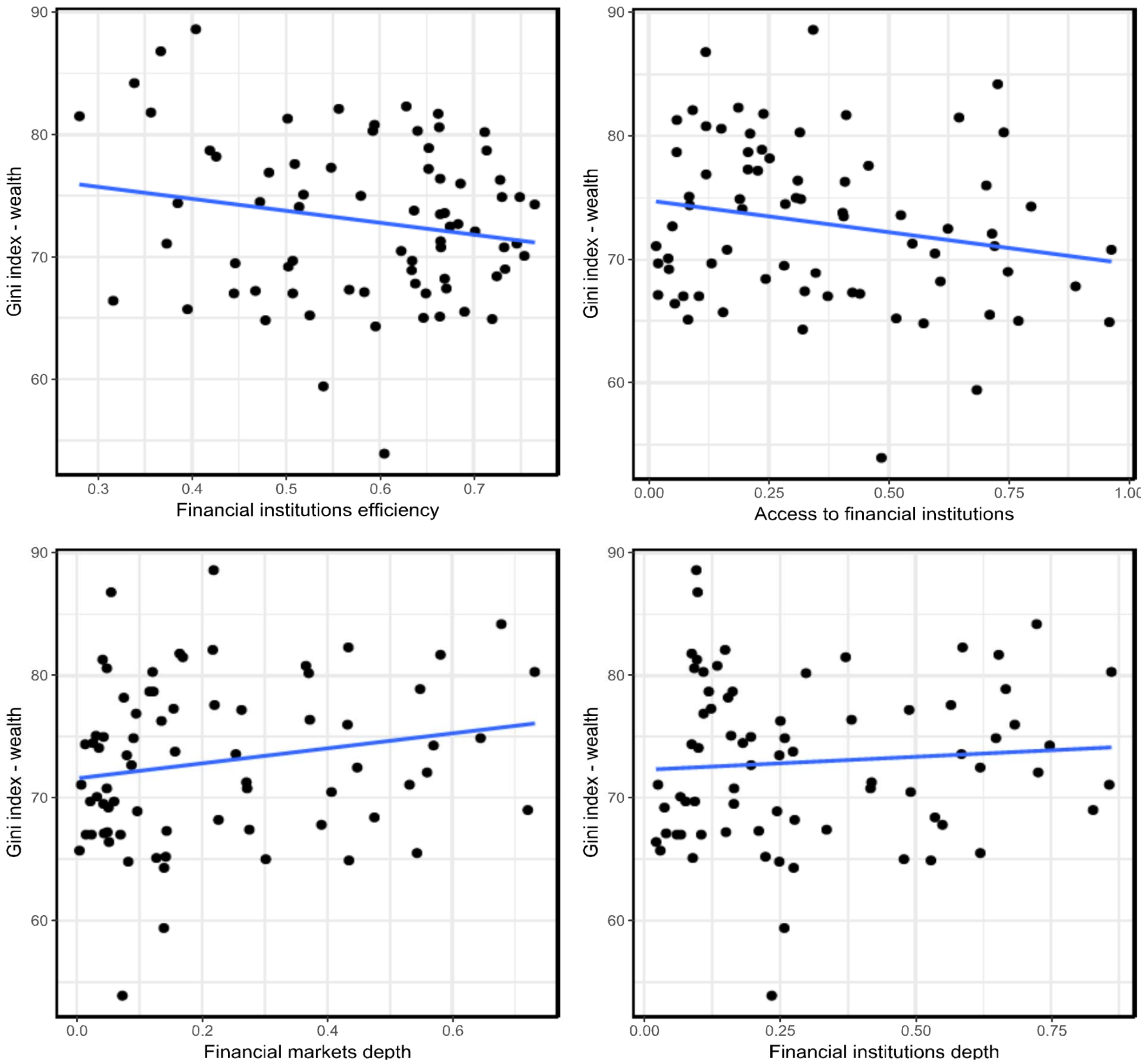
5. Results

In this section, we first present several scatter plots to visualize the relations between financial development indicators and wealth inequality. Second, we present BMA results regarding the determinants of wealth inequality, and third, we address endogeneity issues using IVBMA.

Figure 1 offers an initial insight into the relationship between financial indexes and wealth inequality. The scatter plots show an expected pattern. We observe efficiency of intermediation and access to financial services to be negatively correlated with inequality. On the other hand, Figure 1 suggests that the depth of financial markets is higher in countries with higher wealth inequality. The depth of financial institutions exhibits a slightly weaker but still positive relationship. Overall, the scatter plots suggest that there is some relation between financial development indicators and wealth inequality and that this relation is complex, i.e., some aspects of financial development may contribute to greater wealth inequality, whereas other aspects exert an opposite effect.

Table 4 presents our BMA results regarding the determinants of wealth inequality. We present the explanatory variables sorted by their pip values. According to our results, only a handful regressors robustly determine the cross-country variation in wealth inequality and exhibit pip greater than 0.5. Financial development indicators represent nearly half of these regressors, suggesting that finance is a crucial factor for understanding wealth inequality. Examining our global sample, our results suggest that cross-country differences in wealth inequality are a combination of effects stemming from finance, globalization, education, advances in agriculture and redistribution. But quantitatively, how important is this set of regressors in explaining wealth inequality? If we estimate the simple OLS regression with regressors exhibiting pip greater than 0.5, we find the corresponding value of R-squared to be 0.56 (adjusted R-squared to be 0.51). This result suggests that we can explain approximately half of the variation in the cross-country differences in wealth inequality using only the seven most relevant regressors. We discuss the effects of individual regressors in detail below.

Figure 1: Finance and Wealth Inequality



Note: Selected financial development indicators presented.

The variables with high pip exhibit the expected qualitative effects on wealth distribution. The greater efficiency of financial intermediation and better access to the financial institutions results in a more uniform distribution of wealth. This finding is broadly in line with the conclusion of Claessens and Perotti (2007) regarding the determinants of income inequality, who assert that access to financial resources is a key driver in reducing income inequality rather than the depth of the financial market. The result of Claessens and Perotti (2007) also accords with the lower PIP of financial institutions depth in our model.

According to our results, large financial markets (i.e., more capitalized stock markets and greater debt securities markets) propagate differences in wealth. Stock price booms are likely to increase wealth inequality because of the composition of household wealth, as stocks are typically owned by rich households. Kuhn et al. (2017) provide new estimates of wealth inequality in the US from 1949–2016 based on archival data from the Survey of Consumer Finances and examine the evolution of wealth over time. Their results are in accordance with ours: stock price booms indeed contribute to greater wealth inequality.

In addition, one could argue that our result regarding the effect of the size of financial markets on wealth inequality corresponds to recent findings suggesting that too much finance is harmful to growth (Arcand et al., 2015; Cecchetti and Kharroubi, 2012; Law and Singh, 2014) and that it is important to disentangle quantity and quality of finance when examining the effect of finance on growth (Hasan et al., 2018). However, this analogy is only partially valid because whereas we typically think of greater economic performance as a positive phenomenon, there is a uncertainty about what is the ‘optimal’ level of wealth inequality.

Outward orientation capturing the openness of the economy leads to higher levels of wealth inequality. Large importance and qualitative effect correspond to the earlier findings, such as those of Dabla-Norris et al. (2015), which claim that globalization and increasing exposure to the outside world contributes to greater within-country inequality. If globalization increases growth, then this result implies that the globalization benefits some economic agents more than others. For example, Dabla-Norris et al. (2015) and Milanovic (2016) mention the skill premium related to technological progress, which leads to excessive earnings and widens inequality. Nevertheless, our results provide little evidence that technological progress increases wealth inequality. We use a comprehensive index of technological progress developed by Comin and Hobijn (2010), but as we can observe from Table 4, its PIP is very low. We attribute our result regarding the effect of technological progress on wealth inequality to the sample that we use. Our global sample covers countries with different degrees of economic development and technological progress, and it is likely that technological progress may play a greater role specifically in the most advanced countries.

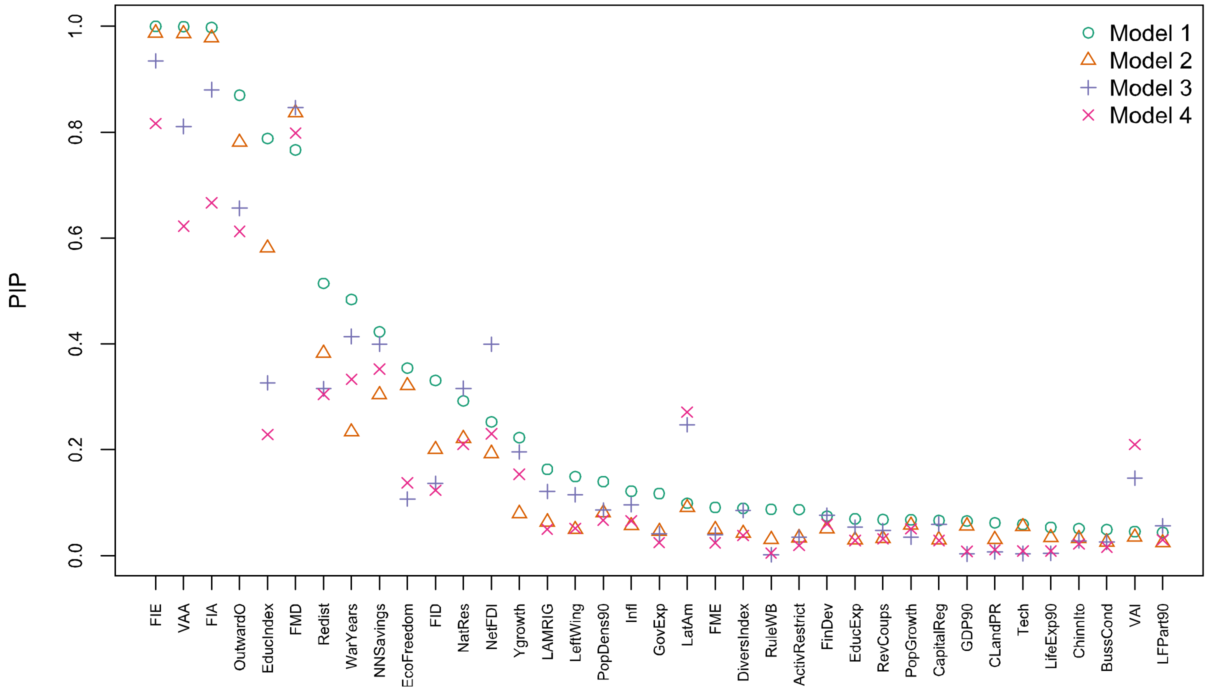
Table 4: Determinants of Wealth Inequality, BMA Estimation

	PIP	Post Mean	Post SD
Financial institutions efficiency	1.00	–0.33651	0.11350
Value added in agriculture	1.00	–0.51800	0.16188
Access to financial institutions	1.00	–0.38266	0.15020
Outward orientation	0.87	0.20663	0.12371
Education index (UN)	0.79	–0.26055	0.20440
Financial market development	0.77	0.34023	0.23533
Redistribution	0.51	–0.10670	0.13963
Number of war years	0.48	0.06956	0.09701
Net national savings	0.42	0.08447	0.13021
Economic freedom index (adjusted)	0.35	–0.08233	0.15183
Financial institutions development	0.33	0.14210	0.24598
Natural resource rents	0.29	0.04572	0.09402
Net foreign direct investment	0.25	–0.03291	0.07552
Average GDP growth	0.22	–0.02607	0.06759
Labor market regulation	0.16	0.01630	0.05386
Leftwing orientation	0.15	–0.01239	0.04533
Population density	0.14	–0.01540	0.05521
Inflation	0.12	0.01036	0.04442
Government expenditures	0.12	0.01311	0.05717
Latin America dummy	0.10	0.00987	0.04762
Financial markets efficiency	0.09	–0.00706	0.04026
Banking diversification	0.09	–0.00579	0.03217
Rule of law	0.09	0.01368	0.08087
Active banking restrictions	0.09	–0.00612	0.03667
Financial development index (EFW)	0.07	–0.00364	0.04464
Public education expenditures	0.07	0.00363	0.02903
Revolutions and coups	0.07	0.00250	0.02705
Population growth	0.07	0.00394	0.04154
Bank capital regulations	0.07	–0.00323	0.02589
GDP level in 1990	0.07	–0.00809	0.07483
Civ. liberties and pol. rights	0.06	–0.00322	0.04104
Technological progress	0.06	–0.00596	0.06110
Life expectancy	0.05	0.00043	0.04581
Financial openness (Chinn-Ito)	0.05	0.00150	0.03218
Business conditions	0.05	–0.00196	0.02568
Value added in industry	0.05	–0.00030	0.02710
Labor force participation	0.04	0.00054	0.01815

Note: Dependent variable – average Gini index (wealth) 2010–2016, 73 observations, baseline (hyper-g parameter prior)

Redistribution, which we define as the difference between the market and after-tax income Gini indexes, contributes to lower wealth inequality. This result can be interpreted as evidence indicating that government policies may in fact affect inequality despite the well-known difficulties regarding the taxation of top earners. Our results are broadly in line with those of Jakobsen et al. (2018), who find that the abolition of the Danish wealth tax in 1997 contributed to more wealth inequality by increasing the wealth of top earners. Interestingly, the political orientation of the government (as captured by the variable 'left wing orientation') is not robustly related to wealth inequality. This result suggests that deeds (i.e., the actual level of redistribution) rather than words (i.e., stated political orientation) matter.

Figure 2: Robustness Check: Different Prior Structure



Note: Parameter and model prior comparison – compound indicators. Model 1: hyper-g, uniform; Model 2: UIP, uniform; Model 3: hyper-g, dilution; Model 4: UIP, dilution.

Although the variable 'number of war years' exhibits an inclusion probability of slightly less than 0.5, we find wars to be associated with higher wealth inequality. This result is at odds with previous evidence arguing that wars reduce inequality because of enormous capital destruction, inflation and sizable redistributive government programs (to finance the war); see, for example, (Piketty, 2014; Milanovic, 2016) and the references therein. However, this evidence focuses on the effect of war on inequality over time and focuses on substantial and long-lasting conflicts, such as

World War I or II. Our regressions explain cross-sectional variation in wealth inequality, i.e., why inequality is higher in some countries than in others. In addition, our dataset regarding wars is based on the 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 the rule of law, cause violent confiscation of private property by militias 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 inequality increases, but this effect is temporary, and later on, inequality falls slowly back to the steady state.

We report the baseline results, in which we employ the uniform model prior and hyper-g parameter prior, as described in section 4. To provide robustness checks, we also use alternative parameter and model priors. Figure 2 presents a graphical illustration of our robustness checks. We estimate alternative specifications of the model using UIP and the dilution model prior described earlier. Overall, the results are similar. The optional priors slightly decrease pip across the set of regressors, with the combined effect of UIP and dilution model prior having the largest effect. This slight general decrease in inclusion probabilities is related to the smaller models dictated by the alternative prior structures, but the ordering of the variables in terms of pip remains quite stable. The only exception to marginal decreases in the pip is the effect of education, which decreases to less than 0.5 when we apply the dilution model prior in the estimation. This result could be partially explained by the design of this particular prior, which should down-weight variables that are highly correlated with others. We also tried other specifications with quadratic terms of financial indexes, interactions between the rule of law and financial indexes, and others. None of these additional regressors exhibited significant relevance in our model.[13]

Next, we argue that the effect of finance on wealth inequality is complex and whereas some financial indicators decrease the inequality, other financial indicators increase it. But what is the overall effect of finance on wealth inequality? We take the estimated posterior means from Table 4 for the finance variables with PIP values greater than 0.5 (these are access to financial institutions (FIA), their efficiency (FIE), and the depth of stock market (FMD)) and multiply them by the corresponding country-specific values. Given the manner in which our explanatory variables are normalized, this multiplication is identical to examining the change in wealth inequality as a result of one-standard-deviation increases in FIA, FIE, and FMD.

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

We present the results of overall effect of finance on wealth inequality in Figure 2. Even though we do not want to overemphasize the precision of our results, the estimated effect is negative for all countries in our sample, i.e., our results suggest that greater financial development reduces wealth inequality. Nevertheless, we observe some heterogeneity in the estimated effect across the countries. Interestingly, we observe the weakest decreasing effect of finance on wealth inequality for the US.[14]

5.1 Endogeneity issues

In our baseline results, we address endogeneity issues by estimating the effect of lagged regressors on wealth inequality. While wealth inequality is based on the data between 2010–2016, the regressors are based on data prior 2010 and often cover the 1980s, 1990s or 2000s. Therefore, we followed the procedure typical for BMA literature (Christofides et al., 2016; Feldkircher et al., 2014; Hasan et al., 2018).

The question of endogeneity is, however, deeply ingrained in the finance-inequality nexus, and we want to provide additional evidence that the estimated effect of finance on wealth distribution is causal. There are reasons for caution. First, a wealth distribution that is more concentrated at the top may result in more power of incumbents, who lobby for funding of their projects using their political connections and thereby distort the market. Second, making the distribution of income wealth more equal may lead to increased demand for financial services as more individuals seek to invest their savings or take up loans when their wealth provides a satisfactory collateral. If such development leads to increased supply of financial services through, for example, newly installed ATMs and opened institutions, it may manifest as better access to financial services (Beck et al., 2007).

To address the potential endogeneity of the relationship between wealth distribution and financial development, we apply IVBMA. This methodology suggested by Karl and Lenkoski (2012) implements the idea of instrumental variables in a Bayesian framework. It is essentially a two-stage estimation in which model uncertainty is considered in both stages. In the robustness check, we set the depth of financial institutions and access to financial institutions endogenous, as we believe that from our set of financial indicators, these are most the ones most likely affected by the reverse causality issues presented previously.

[14] Alternatively, we assessed the overall effect of finance on wealth inequality based on the estimation of the ordinary least squares model. We selected the explanatory variables that had PIP values in 4 greater than 0.5. The results are largely the same and are available upon request.

Figure 3: Effects of individual financial development components on inequality

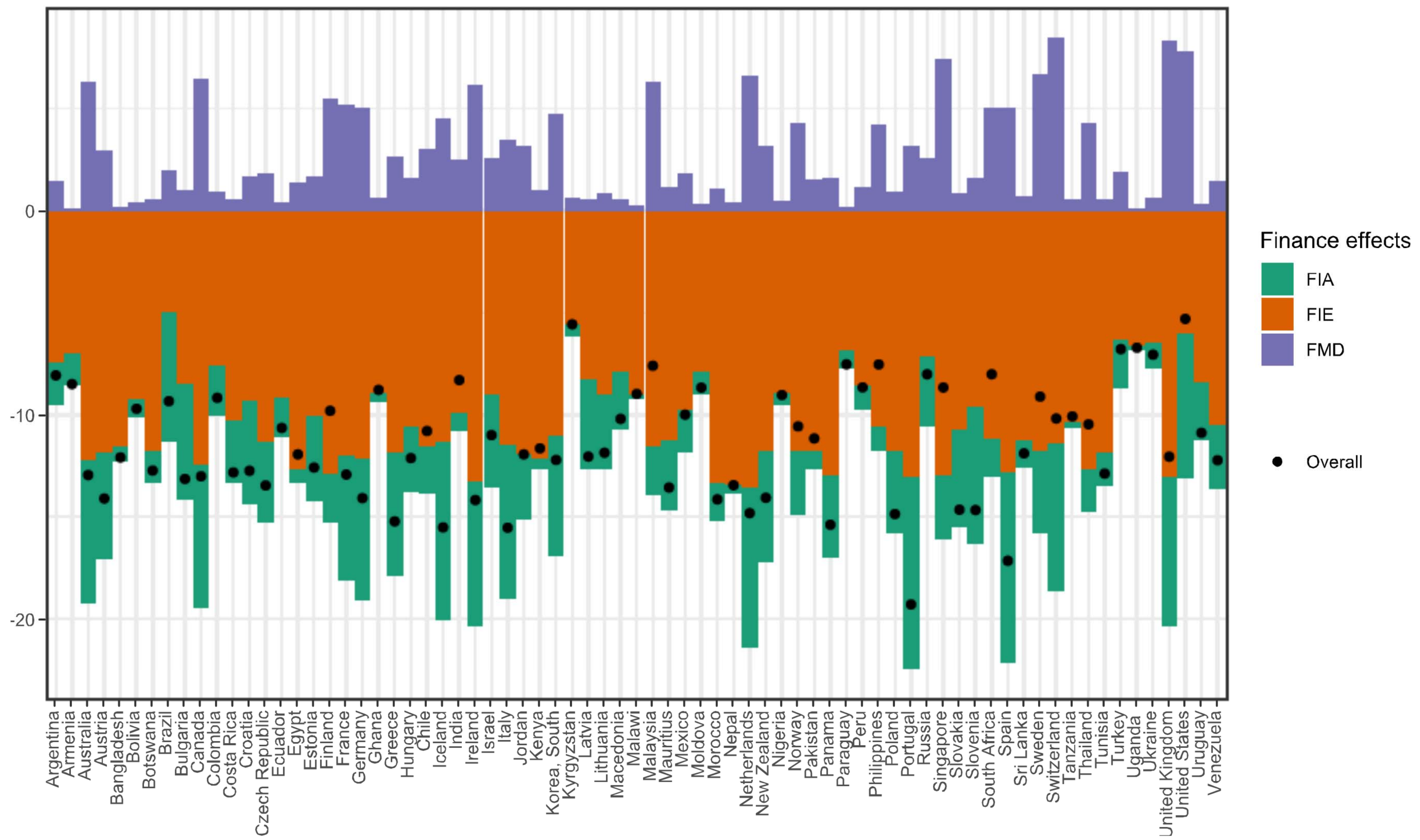


Table 5: Determinants of Wealth Inequality, IVBMA Estimation

	PIP	Post. Mean	Post. SD
Financial institutions efficiency	0.85826	–0.32431	0.18276
Value added in agriculture	0.78741	–0.39918	0.27546
Financial market depth	0.62200	0.29196	0.32026
Financial institutions depth	0.55682	0.24718	0.39989
Outward orientation	0.52022	0.13647	0.15901
Economic freedom index (adjusted)	0.50242	–0.18778	0.24043
Education index (UN)	0.46915	–0.16719	0.23034
Access to financial institutions	0.45168	–0.19051	0.31849
Net national savings	0.42093	0.11213	0.16687
Redistribution	0.39198	–0.10184	0.15932
Natural resource rents	0.36756	0.08280	0.13856
Number of war years	0.36660	0.07267	0.11648
GDP level in 1990	0.29348	–0.03476	0.21811
Latin America dummy	0.25851	0.05039	0.11744
Net foreign direct investment	0.24740	–0.04159	0.09389
Technological progress	0.24198	–0.02756	0.15284
Rule of law	0.22111	0.00025	0.13277
Life expectancy	0.21608	–0.02082	0.12509
Value added in industry	0.20523	0.03081	0.09693
Civ. liberties and pol. rights	0.17607	0.00152	0.08731
Population growth	0.17297	0.01557	0.08178
Inflation	0.17219	0.02180	0.07214
Average GDP growth	0.16884	–0.01947	0.06804
Population density	0.15698	–0.01672	0.06680
Government expenditures	0.15095	0.01087	0.06574
Labor market regulation	0.14337	0.01307	0.05424
Financial openness (Chinn-Ito)	0.13893	–0.00881	0.06817
Leftwing orientation	0.13809	–0.01337	0.04972
Business conditions	0.12686	–0.00665	0.05531
Financial markets efficiency	0.12605	–0.00358	0.05153
Revolutions and coups	0.12206	0.00728	0.04631
Active banking restrictions	0.11903	–0.00620	0.04858
Banking diversification	0.11722	–0.00860	0.04230
Public education expenditures	0.10759	0.00368	0.03795
Bank capital regulations	0.09251	–0.00155	0.03023
Labor force participation	0.09011	–0.00148	0.02810

Note: Dependent variable – average Gini index (wealth) 2010–2016, 73 observations. Financial depth of and access to financial institutions as endogenous. Instruments: genetic distance, financial development index from Economic Freedom of the World.

We employ genetic distance from the United States (Spolaore and Wacziarg, 2009) along with a measure of financial liberalization as instruments. The financial liberalization proxy we construct relies on the components of Economic Freedom of the World (EFW) index by (Gwartney et al., 2017). More specifically, we average the areas 3D, 4C, 4D, and 5A of the EFW. These represent freedom to own foreign currency accounts, black-market exchange rate premium, controls on the movement of capital and people, and credit market regulations. We refer to the authors of EFW for the details of individual components. Although the search for good instruments is a nontrivial exercise, we believe our choice satisfies the basic conditions. Genetic distance should be unrelated to wealth distribution. Even if the primary cause of migration is more/less equal distribution of wealth, it would most likely not be sufficiently substantial to affect the the genetic pattern in a particular country. Additionally, the components of our financial liberalization measure are exogenous to the wealth inequality as the changes in wealth distribution is improbably to have direct effect on any of them. We follow Estevadeordal and Taylor (2013) here, who treat foreign trade liberalization as exogenous.

We check the strength of our instrument by examining the correlations and running simple OLS regressions of our endogenous variable on the instruments. The correlations of the instruments are greater than 0.5 in absolute terms, with the only exception being FID and genetic distance, for which it is –0.37. The regressions reveal strong significance of the instruments and the F-test statistics of the regressions are 35.43 and 19.95 for FIA and FID, respectively. Both values are well above 10, the rule of thumb proposed by Staiger and Stock (1997). We have compared several additional instruments often used in the literature, including the ubiquitously used financial reform index by Abiad et al. (2010) and the legal origin of the countries, but the acefw measure turned out to be the strongest of the instruments.

Table 5 presents the results of the IVBMA estimation. The PIPs of instrumented variables somewhat decrease, in the case of access to financial institutions slightly below 0.5, but it still remains among the most important regressors. We also confirm the the positive effect of financial markets depth along with the high inclusion probability. The PIPs cannot be directly compared with the baseline results due to differences in the estimation procedure. Whereas for the standard BMA we report the inclusion probabilities based on the analytical posterior probabilities of the top models, IVBMA reports the probabilities based on the MC3 sampler. The later approach tends to down weight the PIP for the top and upweight it for the bottom regressors.[15] Overall, the IVBMA estimation largely supports our baseline findings.

[15] If we compare IVBMA output with the MC3 pip from the baseline BMA, we obtain very similar values for both approaches.

6. Concluding Remarks

This paper makes a new contribution to the burgeoning literature about wealth inequality. Whereas the existing literature focuses largely on measurement of wealth inequality (Alvaredo et al., 2013; Davies et al., 2011; Piketty and Zucman, 2014; Saez and Zucman, 2016), we examine a wide array of possible determinants of wealth inequality.

Building the large cross-country dataset, we employ BMA to study the determinants of wealth inequality in order to address the regression model uncertainty. This uncertainty arises from the lack of an encompassing model of wealth inequality, which would dictate the exact regression specification to be estimated. As a side effect, using BMA, we can examine a large number of possible determinants of wealth inequality within a unifying framework. Therefore, we examine how different economic, financial, regulatory, political, social, and institutional variables affect wealth inequality.

Using our global sample, addressing endogeneity issues and subjecting our results to a number of robustness checks, we find that only a handful variables are robustly related to wealth inequality. Our results suggest that cross-country differences in wealth inequality arise due to a combination of the effects stemming from the financial sector, globalization, education, advances in agriculture and government redistribution. More specifically, our baseline estimation shows that there are seven regressors with PIP values greater than 50%, and they explain approximately half of the cross-country differences in wealth inequality.

We find that finance plays an important role in wealth inequality. Out of seven aforementioned variables that are robustly related to wealth inequality, three of them capture the level of financial development. According to our results, finance exerts a complex effect on wealth inequality. Some financial characteristics increase inequality, whereas other financial characteristics, to the contrary, decrease it.

Our results show that large financial markets (as proxied by the stock market capitalization and size of debt securities market type of variables) are associated with greater wealth inequality. This result follows from the composition effect, as it is typically rich households that participate in the stock markets (Kuhn et al., 2017). On the other hand, our findings show that countries with better access to finance and more efficient financial intermediaries exhibit lower wealth inequality. Therefore, there is no natural tendency that financial development results into greater wealth inequality. On the contrary, when we take the average values of financial development measures, the overall effect of finance development on wealth inequality is negative (i.e., more financially developed countries associated with lower level of wealth inequality).

In addition, our results show that more education and greater income redistribution are associated with lower level of wealth inequality. Therefore, this result broadly suggest that governments can affect the inequality within their countries (either via education or taxation). In addition, we also find that (the lack of) political stability influences wealth inequality, as our results show that countries with war experience exhibit greater inequality. Finally, our results suggest that globalization but not technological development is likely to contribute to greater wealth inequality.

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A. Appendix

Additional robustness checks

Table A1: Dependent variable – average Gini index (wealth) 2010–2016, 73 observations, UIP parameter prior

	PIP	Post Mean	Post SD
Financial institutions efficiency	0.99	–0.36999	0.12386
Value added in agriculture	0.99	–0.56485	0.18154
Access to financial institutions	0.98	–0.44382	0.16204
Financial market development	0.84	0.44193	0.23922
Outward orientation	0.78	0.21853	0.14535
Education index (UN)	0.58	–0.23984	0.24290
Redistribution	0.38	–0.10095	0.15101
Economic freedom index (adjusted)	0.32	–0.10501	0.18144
Net national savings	0.30	0.07686	0.13764
Number of war years	0.23	0.03833	0.08335
Natural resource rents	0.22	0.04549	0.10083
Financial institutions development	0.20	0.10354	0.23661
Net foreign direct investment	0.19	–0.03276	0.08044
Latin America dummy	0.09	0.01404	0.05849
Population density	0.08	–0.01162	0.05108
Average GDP growth	0.08	–0.00950	0.04338
Labor market regulation	0.06	0.00671	0.03585
Population growth	0.06	0.00788	0.04715
Inflation	0.06	0.00568	0.03341
GDP level in 1990	0.06	–0.01404	0.08467
Technological progress	0.05	–0.01188	0.07248
Financial development index (EFW)	0.05	–0.00641	0.04430
Financial markets efficiency	0.05	–0.00499	0.03332
Leftwing orientation	0.05	–0.00400	0.02612
Government expenditures	0.05	0.00463	0.03646
Banking diversification	0.04	–0.00316	0.02370
Value added in industry	0.04	0.00229	0.03279
Life expectancy	0.03	–0.00160	0.03867
Active banking restrictions	0.03	–0.00213	0.02262
Revolutions and coups	0.03	0.00178	0.02012
Financial openness (Chinn-Ito)	0.03	–0.00137	0.02553
Rule of law	0.03	0.00093	0.03789
Civ. liberties and pol. rights	0.03	–0.00131	0.02953
Bank capital regulations	0.03	–0.00131	0.01725
Public education expenditures	0.03	0.00113	0.01817
Business conditions	0.03	–0.00000	0.01732
Labor force participation	0.02	0.00028	0.01376

Table A2: Dependent variable – average Gini index (wealth) 2010–2016, 73 observations, dilution parameter prior

	PIP	Post Mean	Post SD
Financial institutions efficiency	0.93	–0.29559	0.14058
Access to financial institutions	0.88	–0.35265	0.19165
Financial market development	0.85	0.38321	0.21129
Value added in agriculture	0.81	–0.37066	0.23301
Outward orientation	0.66	0.15971	0.14225
Number of war years	0.41	0.06813	0.10412
Net national savings	0.40	0.10489	0.15200
Net foreign direct investment	0.40	–0.06582	0.10158
Education index (UN)	0.33	–0.12682	0.20519
Natural resource rents	0.32	0.06267	0.11045
Redistribution	0.32	–0.08372	0.14239
Latin America dummy	0.25	0.04844	0.10292
Average GDP growth	0.20	–0.02656	0.07126
Value added in industry	0.15	0.03229	0.09069
Financial institutions development	0.14	0.06411	0.17325
Labor market regulation	0.12	0.01228	0.04752
Leftwing orientation	0.11	–0.00800	0.03714
Economic freedom index (adjusted)	0.11	–0.03180	0.10542
Inflation	0.10	0.01006	0.04385
Population density	0.09	–0.00999	0.04676
Banking diversification	0.09	–0.00557	0.03201
Financial development index (EFW)	0.08	–0.01339	0.05852
Bank capital regulations	0.06	–0.00114	0.02308
Labor force participation	0.06	–0.00002	0.02089
Public education expenditures	0.05	0.00208	0.02499
Revolutions and coups	0.05	0.00270	0.02436
Government expenditures	0.04	0.00506	0.03702
Financial markets efficiency	0.04	–0.00350	0.02844
Population growth	0.04	0.00542	0.04010
Active banking restrictions	0.03	–0.00191	0.02272
Financial openness (Chinn-Ito)	0.03	–0.00266	0.02558
Business conditions	0.03	0.00043	0.01735
Civ. liberties and pol. rights	0.01	0.00054	0.01473
Life expectancy	0.00	–0.00069	0.01508
Technological progress	0.00	–0.00099	0.02030
GDP level in 1990	0.00	–0.00102	0.02294
Rule of law	0.00	–0.00013	0.00744

Table A3: Dependent variable – average Gini index (wealth) 2010–2016, specific financial indicators as proxies for financial development, 73 observations, dilution parameter prior

	PIP	Post Mean	Post SD
Outward orientation	1.00	0.30288	0.09493
Value added in agriculture	1.00	–0.46969	0.16524
Number of war years	1.00	0.23140	0.09211
Bank branches/1000 inh.	0.99	–0.23286	0.10392
Redistribution	0.96	–0.27204	0.13368
Private credit	0.80	0.26709	0.20234
Average GDP growth	0.72	–0.12719	0.11806
Net interest margin	0.71	0.26047	0.23046
Business conditions	0.63	–0.16526	0.17583
Inflation	0.52	0.08140	0.10963
Education index (UN)	0.43	–0.09997	0.16364
Economic freedom index (adjusted)	0.38	–0.11007	0.18830
Leftwing orientation	0.26	–0.02542	0.06428
Labor market regulation	0.17	0.01351	0.04931
Rule of law	0.17	0.02859	0.11191
Net national savings	0.16	0.01665	0.06290
Natural resource rents	0.16	0.01609	0.06250
Bank Z-score	0.15	0.01193	0.04857
Latin America dummy	0.13	0.01040	0.05422
Banking diversification	0.12	–0.00670	0.03591
Market capitalization	0.11	0.00106	0.04334
Market turnover	0.11	0.00559	0.03372
Civ. liberties and pol. rights	0.11	0.00419	0.05246
Value added in industry	0.11	0.00610	0.04528
Population growth	0.11	0.00659	0.05385
Life expectancy	0.10	–0.00578	0.06521
Technological progress	0.10	0.00530	0.08492
Financial development index (EFW)	0.10	0.00203	0.05079
Net foreign direct investment	0.10	–0.00504	0.03344
GDP level in 1990	0.10	0.00277	0.08595
Financial openness (Chinn-Ito)	0.09	0.00422	0.04314
Public education expenditures	0.09	0.00437	0.03492
Government expenditures	0.09	0.00648	0.04413
Loan-to-deposits	0.09	0.00400	0.03650
Revolutions and coups	0.09	0.00307	0.03130
Active banking restrictions	0.08	0.00076	0.03139
Bank capital regulations	0.08	–0.00113	0.02484
Population density	0.07	0.00112	0.02579
Labor force participation	0.07	–0.00105	0.02323

Dataset description

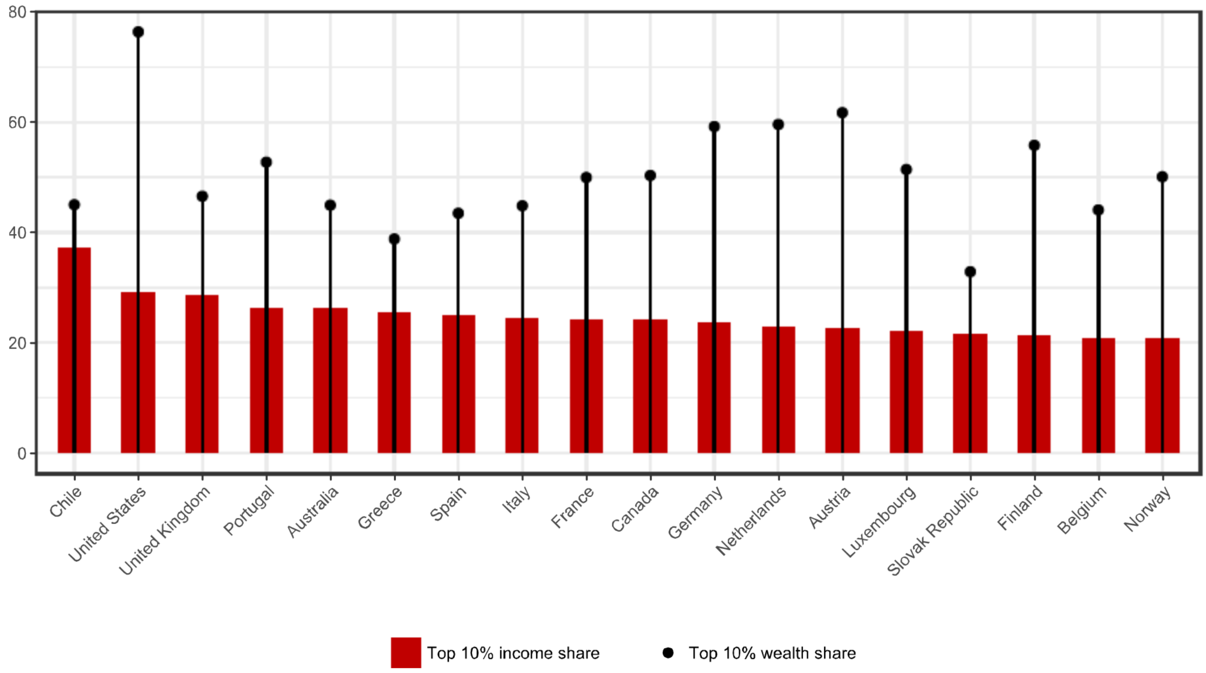
Table A4: List of variables

Variable	Definition (+ optional comments)	Source
GiniWealth	Gini index based on the distribution of wealth from Credit Suisse Wealth Reports 2010–2016	Credit Suisse
FIA	Access to financial institutions	Svirydzenka (2016)
FID	Financial institutions depth	Svirydzenka (2016)
FIE	Financial institutions efficiency	Svirydzenka (2016)
FMD	Financial markets depth	Svirydzenka (2016)
FME	Financial markets efficiency	Svirydzenka (2016)
NatRes	Total natural resource 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 Labor Organization definition of the economically active population: all people who supply labor for the production of goods and services during a specified period. Labor 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)

Table A4 (continued)

Variable	Definition (+ optional comments)	Source
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)
FST	Genetic distance data (distance from the US)	Spolaore and Wacziarg (2009)
FinReform	Financial reform index by Abiad (2010)	Abiad et al. (2010)
FinLib	Averaged components of Economic Freedom of the World index 3D (freedom to own foreign currency accounts), 4C (black-market exchange rates), 4D (controls of the movement of capital and people), and 5A (credit market regulations).	Gwartney et al. (2017)

Figure A1: Top 10% wealth and income shares in OECD countries



Note: Source: Author based on the OECD

Bayesian Model Averaging

First, consider the following linear model:

$$y = \alpha + X\beta + \varepsilon \qquad \varepsilon \sim N(0, \sigma^2 I) \tag{A1}$$

where y represents 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 takes into consideration all possible combinations of X from equation A1 and takes a weighted average of the estimated coefficients. Even with a modest-sized regression model, the number of combinations rises dramatically, and even with current computers, it is impossible to estimate all regression models. For this reason, a subset of models is considered, and an MCMC sampler is employed (we discuss the sampler in detail below). The substructure of the model is as follows:

$$y = \alpha_i + X_i\beta_i + \varepsilon \qquad \varepsilon \sim N(0, \sigma^2 I) \tag{A2}$$

X_i corresponds to a subset of X, and α_i and β_i are the corresponding coefficients. If the number of regressors is K, the total number of models equals 2^K, and $i \in [1, 2^K]$.

Bayes' rule implies that

$$p(\beta|y, X) = \frac{p(y, X|\beta)p(\beta)}{p(y, X)} \tag{A3}$$

where $p(\beta|y, X)$ is the posterior density, $p(y, X|\beta)$ is the marginal likelihood (ML), $p(\beta)$ is the prior density, and $p(y, X)$ is the probability of the data.

The individual regression models are denoted as $M_1, \dots, M_i$. In the case of K regressors, there are $M_1, \dots, M_i$ regression models, where $i \in [1, 2^K]$. The model is formed using a likelihood function and a prior density, where M_i depends on the parameters β_i, with a posterior probability to be derived in the following manner:

$$p(\beta_i|M_i, y, X) = \frac{p(y|\beta_i, M_i, X)p(\beta_i|M_i)}{p(y|M_i, X)} \tag{A4}$$

Next, we describe the averaging principle of BMA and individual components of equation A3.

Posterior Model Probability

The posterior model probability (PMP) provides the weights for averaging model parameters across the individual models. The PMP also arises from Bayes' theorem:

$$p(M_i|y,X) = \frac{p(y|M_i,X)p(M_i)}{p(y|X)} \tag{A5}$$

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 because it is constant across all models under consideration. The PMP then becomes directly proportional to ML and the prior probability. The prior probability $p(M_i \propto 1)$ is typically set to acknowledge that the 'true' model is unknown.

$$p(M_i|y,X) \propto p(y|M_i,X)p(M_i) \tag{A6}$$

We discuss the calculation of ML in detail in section A11. Researchers must set the model prior to reflect the beliefs regarding the data before inspecting them.

Posterior Mean

The parameter point estimates are derived within the Bayesian framework as follows. Zeugner (2011) and Moral-Benito (2012) show that the weighted posterior distribution of any statistic (most notably the β coefficients) is obtained as follows:

$$p(\beta|y,X) = \sum_{i=1}^{2^K} p\,(\beta_i|M_i,y,X)p(M_i|y,X) \tag{A7}$$

where $p(M_i|y,X)$ is the PMP of the corresponding model M_i from equation A5. The point estimates are obtained by taking expectations:

$$E(\beta|y,X) = \sum_{i=1}^{2^K} E\,(\beta_i|M_i,y,X)p(M_i|y,X) \tag{A8}$$

$E(\beta|y,X)$ represents the average 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 depends on the choice of the prior g. Zeugner (2011) expresses the expected value of the parameter in M_i as follows:

$$E(\beta_i|y,X,g,M_i) = \frac{g}{1+g}\widehat{\beta_\iota} \qquad \text{(A9)}$$

with $\widehat{\beta_\iota}$ corresponding to the standard OLS estimate.

Posterior Variance

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

$$\begin{aligned} Var(\beta|y,X) \quad &= \sum_{i=1}^{2^K} p\,(M_i|y,X)Var(\beta_i|M_i,y,X) \\ &+ \sum_{i=1}^{2^K} p\,(M_i|y,X)(E(\beta_i|M_i,y,X) - E(\beta|y,X))^2 \end{aligned} \qquad \text{(A10)}$$

The variance consists of two terms: the weighted average of variance estimates across different models $Var(\beta_i|M_i,y,X)$ and the weighted variance across different models in the second component $E(\beta_i|M_i,y,X) - E(\beta rty,X))^2$. $E(\beta|y,X)$ represents the posterior mean from equation A8. As a result, BMA accounts for uncertainty regarding the parameter estimates that arise due to differences across models in addition to the uncertainty of individual models. Zeugner (2011) derives how the value of the prior g affects the posterior variance of the parameters:

$$\begin{aligned} &Cov(\beta_i|y,X,g,M_i) \\ &\qquad = \frac{(y-\bar{y})'(y-\bar{y})}{N-3}\frac{g}{1+g}\left(1 \right. \\ &\qquad \left. - \frac{g}{1+g}R_i^2\right)(X_i{}'X_i)^{-1} \end{aligned} \qquad \text{(A11)}$$

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

Marginal Likelihood

ML can be calculated using equation A4 for each model M_i. Both sides of the equation must be integrated with respect to β_i. Employing $\int_\beta p\,(\beta_i|M_i,y,X)\,d\beta_i = 1$, it follows that

$$p(y|M_i,X) = \int_\beta p\,(y|\beta_i,M_i,X)p(\beta_i|M_i,X)\,d\beta_i \tag{A12}$$

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 also utilize in this paper. The ML for a single model can then be expressed using the prior as in Feldkircher and Zeugner (2009):

$$p(y|M_i,X,g) = \int_0^\infty \int_\beta p\,(y|\beta_i,\sigma^2,M_i)p(\beta_i,\sigma^2|g)\,d\beta d\sigma \tag{A13}$$

Furthermore, Feldkircher and Zeugner (2009) show that ML is in this case simply proportional to

$$p(y|M_i,X,g) \propto (y-\bar{y})'(y-\bar{y})^{-\frac{N-1}{2}}(1+g)^{-\frac{k_i}{2}}\left(1-\frac{g}{1+g}R_i^2\right)^{-\frac{N-1}{2}} \tag{A14}$$

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 A11, i.e., the number of observations and the mean of vector y, respectively.

Posterior Inclusion Probability

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

$$PIP = p(\beta_k \neq 0|y,X) = \sum_{i=1}^{2^K} p\,(M_i|\beta_k \neq 0,y,X) \tag{A15}$$

MCMC Sampler

One of the limitations of BMA is its computational difficulty when the number of potential regressors K becomes very large. Historically, the computational burden has been the primary factor preventing researchers from employing Bayesian methods Zeugner (2011) notes that for small models, it is possible to enumerate all variable combinations. However, 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) as follows:

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:

$$p_{i,j} = min\left(1, \frac{p(M_j|y, X)}{p(M_i|y, X)}\right) \tag{A16}$$

If model M_j is rejected, the next model M_k is suggested and compared with M_i. With an increasing 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 construct 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.