CHARLES UNIVERSITY
FACULTY OF SOCIAL SCIENCES
Institute of Economic Studies

DISSERTATION

Three Essays on Financial Development

Provisional version for pre-defense

Author: Mgr. Jan Mareš

Supervisor: prof. Roman Horváth, Ph.D.

Year of defense: 2020

Declaration of Authorship

The author hereby declares that he or she compiled this thesis independently, using only the listed resources and literature, and the thesis has not been used to obtain any other academic title.

The author grants to Charles University permission to reproduce and to distribute copies of this thesis in whole or in part and agrees with the thesis being used for study and scientific purposes.

Prague, February 15, 2020

_____

Mgr. Jan Mareš

Contents

List of Tables

List of Figures

Acronyms

BIC	Bayesian Information Criterion
BMA	Bayesian Model Averaging
BRIC	Bayesian Risk Inflation Criterion
CBF	Conditional Bayes Factor
CSWD	Credit Suisse Wealth Databook
DINA	Distributional National Accounts
EFW	Economic Freedom of the World
GDP	Gross Domestic Product
GFDD	Global Financial Development Database
HBS	Household Balance Sheet
IID	Independent Identically Distributed
IVBMA	Instrumental Variable Bayesian Model Averaging
LIS	Luxembourg Income Study
MCMC	Markov-chain Monte Carlo
ML	Marginal Likelihood
OECD	Organisation for Co-operation and Development
OLS	Ordinary Least Squares
PIP	Posterior Inclusion Probability
PMP	Posterior Model Probability
PWT	Penn World Table
SWIID	Standardized World Income Inequality Database
UIP	Unit Information Prior
UK	United Kingdom
US	United States
WALS	Weighted-average Least Squares
WB	World Bank
WID	World Inequality Database
WIID	World Income Inequality Database

Chapter 1

Summary of the dissertation

Chapter 2

What Type of Finance Matters for Growth? Bayesian Model Averaging Evidence

Abstract

We examine the effect of finance on long-term economic growth using Bayesian model averaging to address model uncertainty in cross-country growth regressions. The literature largely focuses on financial indicators that assess the financial depth of banks and stock markets. We examine these indicators jointly with newly developed indicators that assess the stability and efficiency of financial markets. Once we subject the finance-growth regressions to model uncertainty, our results suggest that commonly used indicators of financial development are not robustly related to long-term growth. However, the findings from our global sample indicate that one newly developed indicator – the efficiency of financial intermediaries – is robustly related to long-term growth.

2.1 Introduction

Numerous studies investigate the effect of financial development on economic growth and predominantly conclude that there is a positive causal relationship between the two (Atje & Jovanovic, 1993; King & Levine, 1993; Levine & Zervos, 1998). Nevertheless, some opposing views hold that the financial sector removes scarce resources from the rest of the economy (Bolton et al., 2011; Tobin, 1984) and encourages to greater exposure and vulnerability to crises, thus severely burdening the real sector during periods of instability (Kindelberger, 1978; Minsky, 1991; Stiglitz, 2000). The effect of financial development on growth has recently drawn greater attention again because of the financial crisis that began in 2007-2008. Moreover, conclusions referring to diminishing and eventually negative returns from financial development have become increasingly common in the literature (Arcand et al., 2015; Cecchetti & Kharroubi, 2012; Law & Singh, 2014). This highlights the importance of the financial sector for the functioning of the economy and has provoked extensive debate among policymakers.

This paper evaluates the finance-growth nexus but differs from existing research in two main respects. First, it employs BMA to overcome certain drawbacks of previous research approaches. BMA is well grounded in statistical theory (Raftery et al., 1997) and addresses the inherent regression model uncertainty, which is quite high in cross-country growth regressions (Durlauf et al., 2008; Fernandez et al., 2001; Sala-I-Martin et al., 2004). The control variables in finance-growth regressions are often selected in a somewhat *ad hoc* manner with reference to certain relevant theories while ignoring other relevant theories.

BMA essentially allows us to control for dozens of potentially relevant determinants of growth within a unifying framework. The variety of theories of economic growth has given rise to a large number of determinants and resulted in substantial uncertainty concerning the true growth model. In essence, the BMA procedure estimates different combinations of explanatory variables and subsequently weights the coefficients using various measures of model fit. As a consequence, BMA also conveniently limits concerns regarding omitted variable bias and its adverse consequences of inconsistently estimated coefficients, an issue that is typically abstracted from in the empirical work on finance and growth. BMA is capable of evaluating numerous possible regressors and estimating their PIP, i.e., the probability that they are relevant in explaining the

dependent variable, in addition to the weighted mean and variance of their corresponding coefficients. While model averaging has become standard in the empirical growth literature (Durlauf et al., 2008; Sala-I-Martin et al., 2004), it has not been applied to study the finance–growth nexus.

Second, we differ from previous research by examining additional financial indicators to appreciate the multidimensionality of financial systems. Importantly, previous research, including recent studies implying that excessive financial development harms growth (Arcand et al., 2015; Cecchetti & Kharroubi, 2012; Law & Singh, 2014), largely focuses on measures of the depth of financial development such as the credit to GDP ratio. We depart from existing literature in jointly examining whether the depth, stability or efficiency of financial markets (or all of them) is crucial for long-term growth. In doing so, we can unify and re-examine previous studies on the finance-growth nexus that show that a) financial development is conducive to growth, b) excessive financial development is not, and c) financial instability has negative consequences for growth.

The theoretical concepts regarding the functions of the financial industry are difficult to operationalize in empirical research, and there is no universal consensus regarding the measurement of financial development (King & Levine, 1993). Although measuring financial development is complex, researchers typically consider only those variables capturing financial depth, such as the credit to GDP ratio or stock market capitalization, to assess the degree of financial development. Financial indicators assessing the degree of financial access, financial stability or the efficiency of the financial industry have largely been ignored in cross-country studies due to data limitations. The newly developed Global Financial Development Database (GFDD) represents a significant improvement in this respect and provides a comprehensive set of financial indicators that reflect various functions and characteristics of the financial sector. In addition to financial depth, the GFDD provides measures of the efficiency and stability of and access to financial markets. Although data availability remains somewhat limited, we extend the existing literature by including these additional dimensions of the financial sector in our regression analysis to more completely evaluate the effect of finance on growth. Specifically, the indicators we use represent the depth, stability, and efficiency of the banking sector and stock markets as defined by Čihák et al. (2013).[1] In addition to the GFDD,

---

[1]We did not include financial access indicators because of data unavailability. In our sample, the data on the proxy variable recommended for financial access by Čihák et al. (2013),

we employ the widely used dataset on the determinants of long-term growth developed by Fernandez et al. (2001), which encompasses over 40 explanatory variables capturing various economic, political, geographical, and institutional indicators.

While it is commonly assumed that causality goes from financial development to economic growth, some scholars argue that a growing financial sector merely follows the increasing needs of the real economy or may be determined simultaneously with growth due to other factors. The quantitative survey of the finance and growth literature by Valickova et al. (2015), for example, indicates that those studies ignoring endogeneity are more likely to report a stronger positive effect of financial development on growth. Although it is likely that a part of endogeneity in finance–growth nexus can be addressed by model averaging procedure (reducing omitted variable bias), we also examine the robustness of our results through specifications that employ the lagged explanatory variables. To the best of our knowledge, this is the first study to combine various characteristics of the financial sector, a rich dataset on growth, and an approach that addresses model uncertainty and endogeneity. As a result, our study addresses two main issues in finance–growth literature: 1) causality issues and 2) measurement of financial development.

Using data on real economic growth in 60 countries between 1960 and 2011, we find that bank efficiency is robustly related to long-term growth and exhibits very high PIP. This finding corresponds to the predictions of theoretical model by Pagano (1993), who shows that the efficiency of financial intermediaries is crucial for funneling savings to investment and therefore, for increasing real growth. The relevance of traditional variables, such as credit provided to the private sector or stock market capitalization, is weaker. In addition, we also fail to find a non-linear effect of financial development on growth. Our results are robust to a series of checks such as employing a different sample period, different parameter priors or addressing endogeneity. Therefore, our results highlight that the approach to measuring financial development is crucial for the estimated effect of finance on growth. Our policy implication is that those managing the current worldwide wave of regulatory changes in the financial

bank accounts per 1,000 adults, are missing for 36 out of 60 countries. Including financial access in the analysis would therefore severely limit our cross-section of countries resulting in the non-negligible loss in the degrees of freedom. Nevertheless, we have examined alternative (less than ideal) financial access indicators from the GFDD database (bank branches per 100,000 adults and ATMs per 100,000 adults), which are available for almost all countries in our sample. However, we fail to find these indicators to be decisive for the long-term growth.

industry should not underestimate the importance of the efficiency of financial intermediaries for long-term growth.

The chapter is structured as follows. Section 2.2 provides a literature review on finance and growth. Section 2.3 presents the data. We describe Bayesian model averaging in Section 2.4. We provide the regression results in Section 2.5. The conclusions are presented in Section 2.6. An appendix with additional results follows.

2.2 Empirical Literature on Finance and Growth

We briefly survey the empirical literature on the effect of financial development on growth. In addition, we discuss certain issues regarding the measurement of financial development. We refer readers to Levine (2005), Ang (2008) and Valickova et al. (2015) for more comprehensive surveys of this literature.[2]

2.2.1 Empirical Evidence

Focusing on the period between 1960 and 1989, King and Levine (1993) show how the initial levels of various financial indicators, such as the liabilities to the financial sector, bank ratios, credit to nonfinancial private sector/total domestic credit, and credit to the private sector to GDP, explain the real growth of GDP per capita, capital accumulation, and efficiency of capital utilization in the following period. Atje and Jovanovic (1993) examine the stock market's effects on economic growth and find that more active stock markets induce growth. The conclusion regarding stock market activity is subsequently confirmed by Levine and Zervos (1998). In addition to providing evidence on stock market effects, Levine and Zervos (1998) simultaneously control for banking sector development by including credit to the private sector. Interestingly, both the banking sector and stock markets are significant in fostering growth. This leads the authors to conclude that each of the sectors has a different function in the economy and a different financial function. Furthermore, they add that the mere size of the stock market as measured by total capitalization is irrelevant to growth and that the relevant factor is the activity of the stock market. Nevertheless, this link may be an outcome of an unobserved third factor that stimulates both trading activity and economic growth. For instance, infor-

---

[2]There is also literature on the determinants of financial development, see Ang (2013), and Ang and Kumar (2014).

mation regarding new technology may spur trading activity due to conflicting opinions on the future benefits of the innovation. The subsequent economic growth is a result of technological advancement rather than greater trading volumes (Levine, 2005). This is one of the reasons why we apply the BMA, which is designed to address these issues.

Rajan and Zingales (1998) initiate the research on the finance-growth nexus using industry-level data. They show that more developed financial markets decrease firms' cost of external capital. They also find evidence that industries that are relatively more dependent on external finance grow faster in countries with better developed financial intermediaries. Building on this methodology, Claessens and Laeven (2005) arrive at a similar conclusion using measures of bank competitiveness. They find that more competitive banking systems benefit financially dependent industries. Next, Beck et al. (2005) show that industries typically composed of small firms enjoy relatively superior growth rates in countries with developed financial sectors. This is consistent with theory positing that financial development is a crucial factor in alleviating financial constraints. Also, Hasan et al. (2009) examine the effect of financial development on regional growth in Europe and find that the efficiency of financial intermediaries (measured by bank efficiency) is substantially more important for growth than financial depth (measured by outstanding credit). Berger et al. (2004) also provide international evidence on the importance of bank efficiency for growth. Similarly, using German data, Koetter and Wedow (2010) find that bank efficiency is positively related to growth. Jayaratne and Strahan (1996) report that the relaxation of bank branch restrictions in the United States improves growth. Interestingly, they find that the relaxation of restrictions does not increase the volume of bank lending but improves loan quality. In addition, Cetorelli and Strahan (2006) extensively examine the mechanism how financial development affect growth and find that more competition among local U.S. banks improves firms' performance.

Panel and time-series analyses predominantly claim that the relationship goes from financial development to growth rather than in the reverse direction, essentially moderating endogeneity concerns. Christopoulos and Tsionas (2004), Fink et al. (2003) and Peia and Roszbach (2015) observe positive long-run growth effects of financial development using cointegration techniques. Christopoulos and Tsionas (2004) argue in favor of long-run causality from financial development to growth and dismisses the backward channel. Fink et al. (2003) is one of the few papers investigating the relationship by considering

private bond markets. Peia and Roszbach (2015) investigate the causality of the finance-growth relationship and demonstrate that the causality depends on the measurement employed and the level of financial development. Recently, Thumrongvit et al. (2013) revisit the question and compare the impact of bond markets while also accounting for the role of the banking sector. They report that the importance of bank credit in determining growth declines as alternative debt financing options become increasingly available. Although studies positing "finance-lead" growth prevail, there are opposing views that stress finance's irrelevance in this respect. Garretsen et al. (2004), for example, document that the causal link reported by Rajan and Zingales (1998) disappears after accounting for societal and legal factors. It may be that the development of financial markets simply follows growth, reflecting the needs of a more developed economy. Ultimately, accounting for time- and country-specific effects does not entirely eliminate the caveats applicable to such analyses. Time coverage is often short, and utilizing more frequent observations, such as quarterly data, does not properly address hypotheses concerning the long-term nature of the relationship (Ang, 2008).

Researchers have devoted greater attention to the finance and growth literature following the economic crisis of 2007-2008. They raise questions regarding possible non-linearities in the relationship between finance and growth, specifically, whether excessive financial development is harmful to growth. Rousseau and Wachtel (2011) report that a positive correlation between the development of the financial sector and economic growth is typical for the period before 1990. The effect diminishes when subsequent years are considered. Additional studies report evidence of an inverted U-shaped relationship suggesting financial development is conducive to growth only up to a certain threshold. Thereafter, it acts as a drag on economic growth (Arcand et al., 2015; Cecchetti & Kharroubi, 2012; Law & Singh, 2014). Some research advances explanations to justify these findings. One is the comparatively large amount of credit going to households in the later stages of financial development. These loans generally tend to be less productive than loans to enterprises (Beck et al., 2012). Cecchetti and Kharroubi (2013) emphasize that a larger financial sector leads to lower total factor productivity through relatively larger benefits for high-collateral/low-productivity projects, primarily in construction. Other lines of reasoning rely on Tobin's early work discussing how finance lures talent from other sectors (Bolton et al., 2011; Cecchetti & Kharroubi, 2012; Kneer, 2013). Yilmazkuday (2011) shows that growth enhancing effect of finance de-

pends on a number of factors such as price stability, economic development or
trade openness. Overall, these recent empirical studies find that the growth-
enhancing effects of financial development are not guaranteed and suggest that
the relationship is more complex than originally thought.

2.2.2 Measurement of Financial Development

Levine (2005) argues that it is difficult to link empirical and theoretical research
on finance and growth. Concepts such as information asymmetry, improved
corporate governance, risk management, pooling savings, and easing exchange
are in reality difficult to measure accurately.

The most common indicators of financial development address financial
depth, primarily because of their widespread availability. Conventional vari-
ables used as proxies for the depth of the financial sector are total liquid liabili-
ties of the financial sector, credit to the private sector, and various measures of
monetary aggregates. The aforementioned variables depict the development of
the banking sector, in stock market studies, broadly employed proxies include
the ratio of total market capitalization to GDP, the total value traded to GDP
(stock market activity ratio), and the total value traded to the total value of
listed shares (turnover ratio).

The extent to which these traditional measurements reflect the ability of
financial intermediaries to serve the functions assigned to them in theory re-
mains unclear. For instance, Čihák et al. (2013) illustrate that private bond
market capitalization represents a substantial share of the total securities mar-
ket capitalization within a country. However, when addressing the question of
depth, private bond markets are often ignored. In addition, total credit data
do not include trade credit, where firms *de facto* act as financial intermediaries
(Petersen & Rajan, 1997). In addition, Levine (2005) notes that this factor
may be particularly important in countries with poor legal environments or
overly regulated financial systems. Ultimately, there is no general consensus
among researchers regarding the appropriate approach to measure financial de-
velopment. Generally, studies consider several potential indicators to assess
the robustness of their results, but these indicators are typically only proxies
for the level of financial depth (Valickova et al., 2015).

Finally, some financial development measures such as the (rarely used)
bank efficiency can be conceptually much more closely related to the theory
(Pagano, 1993) than the traditional quantity measures such as the volume of

credit granted. Bank efficiency is also less likely to be prone to causality issues because technical efficiency of banks respond less to the business cycle in comparison to, for example, the volume of credit (Koetter & Wedow, 2010).

2.3 Data

We use the dataset from a seminal paper on long-term economic growth determinants and BMA by Fernandez et al. (2001). The dataset contains 41 explanatory variables that might be important for growth in 72 countries. We update the dependent variable (average real economic growth per capita in 1960-2011). The regressors in the dataset comprise various measures of economic, political, geographic, demographic, social, and cultural factors. As many of these factors may be determined simultaneously with growth, the regressors typically come from 1960 or even before to alleviate endogeneity concerns. We describe this dataset in greater detail in the appendix.

To this dataset, we add selected financial indicators from the World Bank's GFDD (September 2013 version), which collects information on various aspects of financial sectors around the globe. Čihák et al. (2013) describe this dataset's content in detail and offer a 4x2 dimensional classification of financial indicators that reflects their utility in representing the depth, breadth, efficiency, and stability (4) of both the banking sector and the stock market (2). We choose to employ several indicators for which the database provides the richest data. Specifically, we select five different indicators representing various aspects of the financial system:

- **Private sector credit to GDP:** domestic private credit to the real sector to GDP; a measure of the depth of the banking sector.

- **Stock market capitalization to GDP:** value of listed shares to GDP; a measure of the depth of stock markets.

- **Net interest margin:** accounting value of banks' net interest revenue as a share of average interest-bearing assets; a measure of the efficiency of the banking sector.

- **Stock market turnover ratio:** stock market value traded to total market capitalization; a measure of the efficiency of stock markets.

- **Bank Z-score:** return on banks' assets plus the ratio of banks' equity and assets, divided by the standard deviation of the return on assets $\left(\frac{ROA+\frac{equity}{assets}}{sd(ROA)}\right)$; a measure of the stability of the banking sector.

The aforementioned dimensional distinction allows us to differentiate and compare the effects of the banking sector and the stock market on economic growth. In addition, unlike the previous literature, we simultaneously examine whether the depth, efficiency and stability of a financial system are important for growth.

The time and cross-country coverage of financial variables varies. Private credit to the real sector is available for the majority of the countries in the dataset since 1960. However, the remaining variables are typically available only from the 1980s onward. We average the indicator values corresponding to a selected period (i.e., 1960-2011) and to their data availability. This is a standard procedure in estimating empirical long-term growth models, despite the risk of introducing endogeneity into the model and information loss introduced by averaging over extended time periods. The benefit of averaging is a focus on long-term trends while abstracting from short-term fluctuations. But in our robustness checks, we also use the initial values of financial indicators instead of their average. Given the data availability and the construction of the dataset, all the financial variables could be endogenous. We address endogeneity concerns through our BMA approach using lagged variables. Table 2.1 presents descriptive statistics on the individual financial indicators. Overall, the combined dataset of Fernandez et al. (2001) and private credit and new financial indicators leads to 68 and 60 observations, respectively.

Table 2.1: Descriptive statistics, financial indicators

	Min	Max	Mean	Std.dev
Net interest margin	0.59	13.31	4.52	3.25
Bank Z-score	-1.61	42.35	15.00	9.62
Private credit	5.16	146.66	46.58	35.29
Market capitalization	0.67	303.77	51.28	52.98
Market turnover	0.96	197.50	48.22	47.13

2.4 Bayesian Model Averaging

To illustrate the application of BMA, we begin with a traditional linear model structure:

$$y = \alpha + X\beta + \varepsilon \qquad \varepsilon \sim N(0, \sigma^2 I) \qquad (2.1)$$

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. In many applications, the list of potentially relevant regressors can be large. In the typical case in which the true regression model is unknown, its construction often begins by including all the variables in the model. However, this strategy is likely to yield imprecise estimates, as the large number of regressors inflates standard errors. Empirical research typically addresses this issue by sequentially eliminating the least significant explanatory variables on the basis of statistical tests to arrive at the single best model with all the irrelevant regressors omitted.

The process described above entails the risk of the researcher retaining an irrelevant variable or dropping an important variable. Koop (2003) emphasizes that the probability of making such mistakes increases rapidly with the number of sequences performed. The various iteration paths may also lead to different regression model specifications. In addition, even if we assume that this procedure identifies the 'best' model, it is rarely acceptable to present only the results from the single 'best' model and disregard the results of 'second-best' models. In summary, then, this model-selection approach ignores the model uncertainty that the researcher faces when she or he defines the model. BMA allows the researcher to account for such uncertainty and presents a rigorous method for treating multiple models.

BMA considers all possible combinations of X from equation 2.1 and takes a weighted average of the coefficients (see also the remarks on the MCMC sampler below). The substructure of the model can be captured as follows:

$$y = \alpha_i + X_i \beta_i + \varepsilon \qquad \varepsilon \sim N(0, \sigma^2 I) \qquad (2.2)$$

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 $i \in [1, 2^K]$.

Researchers are interested in describing coefficients based on observed data.

It follows from Bayes' rule that

$$p(\beta|y, X) = \frac{p(y, X|\beta)p(\beta)}{p(y, X)} \tag{2.3}$$

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:

$$p(\beta_i|M_i, y, X) = \frac{p(y|\beta_i, M_i, X)p(\beta_i|M_i)}{p(y|M_i, X)} \tag{2.4}$$

The following subsections describe the averaging principle of BMA and individual components of equation 2.3.

2.4.1 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:

$$p(M_i|y, X) = \frac{p(y|M_i, X)p(M_i)}{p(y|X)} \tag{2.5}$$

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.

$$p(M_i|y, X) \propto p(y|M_i, X)p(M_i) \tag{2.6}$$

We discuss the calculation of ML in detail in Subsection 2.4.4. The model

prior needs to be elicited by the researcher and reflects the initial beliefs before inspecting the data.

2.4.2 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:

$$p(\beta|y, X) = \sum_{i=1}^{2^K} p(\beta_i|M_i, y, X)p(M_i|y, X) \tag{2.7}$$

where $p(M_i|y, X)$ is the PMP of the corresponding model M_i from equation 2.5. The point estimates can be acquired by taking expectations across the equation:

$$E(\beta|y, X) = \sum_{i=1}^{2^K} E(\beta_i|M_i, y, X)p(M_i|y, X) \tag{2.8}$$

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:

$$E(\beta_i|y, X, g, M_i) = \frac{g}{1+g}\hat{\beta}_i \tag{2.9}$$

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

2.4.3 Posterior Variance

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

$$Var(\beta|y, X) = \sum_{i=1}^{2^K} p(M_i|y, X)Var(\beta_i|M_i, y, X)+$$
$$+ \sum_{i=1}^{2^K} p(M_i|y, X)(E(\beta_i|M_i, y, X) - E(\beta|y, X))^2 \tag{2.10}$$

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 2.8. 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:

$$Cov(\beta_i|y, X, g, M_i) = \frac{(y - \bar{y})'(y - \bar{y})}{N - 3} \frac{g}{1 + g} \left(1 - \frac{g}{1 + g} R_i^2\right) (X_i' X_i)^{-1} \quad (2.11)$$

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.

2.4.4 Marginal Likelihood

ML can be calculated using equation 2.4 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

$$p(y|M_i, X) = \int_\beta p(y|\beta_i, M_i, X) p(\beta_i|M_i, X)\, d\beta_i \quad (2.12)$$

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):

$$p(y|M_i, X, g) = \int_0^\infty \int_\beta p(y|\beta_i, \sigma^2, M_i) p(\beta_i, \sigma^2|g)\, d\beta d\sigma \quad (2.13)$$

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

$$p(y|M_i, X, g) \propto (y - \bar{y})'(y - \bar{y})^{-\frac{N-1}{2}} (1 + g)^{-\frac{k_i}{2}} \left(1 - \frac{g}{1 + g} R_i^2\right)^{-\frac{N-1}{2}} \quad (2.14)$$

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 2.11, the number of observations and the mean of vector y, respectively.

2.4.5 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:

$$PIP = p(\beta_k \neq 0|y, X) = \sum_{i=1}^{2^K} p(M_i|\beta_k \neq 0, y, X) \qquad (2.15)$$

2.4.6 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 (Ciccone & Jarocinski, 2010; Feldkircher & Zeugner, 2009; 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 2.2 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 in Koop (2003), for example, 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:

$$\beta_i|g \sim \ N(0, \sigma^2(g(X_i'X_i)^{-1}) \qquad (2.16)$$

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 & 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 $g \rightarrow \infty$, $\beta_i \rightarrow \beta_i^{OLS}$. Popular choices include the following:

- UIP; $g = N$.

- Bayesian Risk Inflation Criterion (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 $g \rightarrow \infty$. 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

$$p(M_i) = \theta^{k_i}(1 - \theta)^{K-k_i} \tag{2.17}$$

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 following Fernandez et al. (2001), as it allows us to compare our results to those of their study. However, the uniform model prior tends to assign greater weight to intermediate

model sizes. For illustration, consider our dataset of 42 regressors. The expected model size is $\frac{K}{2} = 21$, but there is clearly a larger number of possible models of size 21 than 1. Specifically, there are 42 possible models of size 1, whereas $\binom{42}{21}$ combinations (more than half a trillion) exist for a model size of 21. Therefore, Ley and Steel (2009b) propose an alternative model prior that is less restrictive regarding the expected model size, drawing parameter θ from the Beta distribution. Their argument is that this alternative better reflects the lack of *a priori* knowledge concerning the model. We use this "random" beta-binomial prior in the specifications designed to check the robustness of our baseline estimations.

A few other model priors may 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). While the uniform and beta-binomial model priors assume that the probability of inclusion of one regressor is independent from an inclusion of another one, some regressors are usually correlated. A simple way of 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:

$$p(M_i) = |R_i|\theta^{k_i}(1-\theta)^{K-k_i} \tag{2.18}$$

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 the models with redundant regressors.[3]

Finally, 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

---

[3]We also run an estimation using the tesselation defined dilution prior, which assigns uniform probabilities to the neighborhoods of models. This construction of model prior reflects the idea of dilution more closely as it dilutes the probability across all, not only some, neighborhood models. For the detailed discussion we refer to George (2010). The resulting PIPs are in general slightly lower compared to the baseline, but the conclusions about our financial indicators remain unchanged. The results are available upon request.

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.[4]

2.4.7   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:

$$p_{i,j} = min\left(1, \frac{p(M_j|y, X)}{p(M_i|y, X)}\right) \tag{2.19}$$

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.

---

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

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.

2.5   Results

This section presents two sets of our main results. The first set examines the effect of private credit to GDP on long-term growth. Our results suggest that this standard measure of financial development - *financial depth* - is not a robust determinant of growth once we account for model uncertainty.

The second set investigates the importance of new financial indicators that capture not only depth, but also stability and efficiency. We present two subsets of results, with the financial indicators averaged over examined period and then with their lagged values, to examine how current financial development is related to future growth. We use the latter approach to address potential endogeneity in the finance-growth relationship.

The third set examines the effect of finance on growth is non-linear and whether some interaction effects among financial indicators matter for growth. Overall, our results suggest that the efficiency of financial intermediaries is robustly related to long-term growth but we fail to find any non-linearities and interaction effects.

2.5.1   Private Credit

Figure 2.1 illustrates the relationship between private credit and economic growth. Linear and quadratic fit, the latter with 95% confidence intervals, is also included. In a preliminary examination of the data, we observe a weak and possibly diminishing relationship between credit and growth.

Table 2.2 presents our baseline results for private credit. We sort the explanatory variables according to their PIPs. We find that the initial level of Gross Domestic Product (GDP) in 1960, the dummy variable for Sub-Sahara, the share of GDP in mining, the fraction of Confucian population, equipment investment, distortions in the exchange rate, and covariates capturing black

Figure 2.1: Private credit and growth, 1960-2011
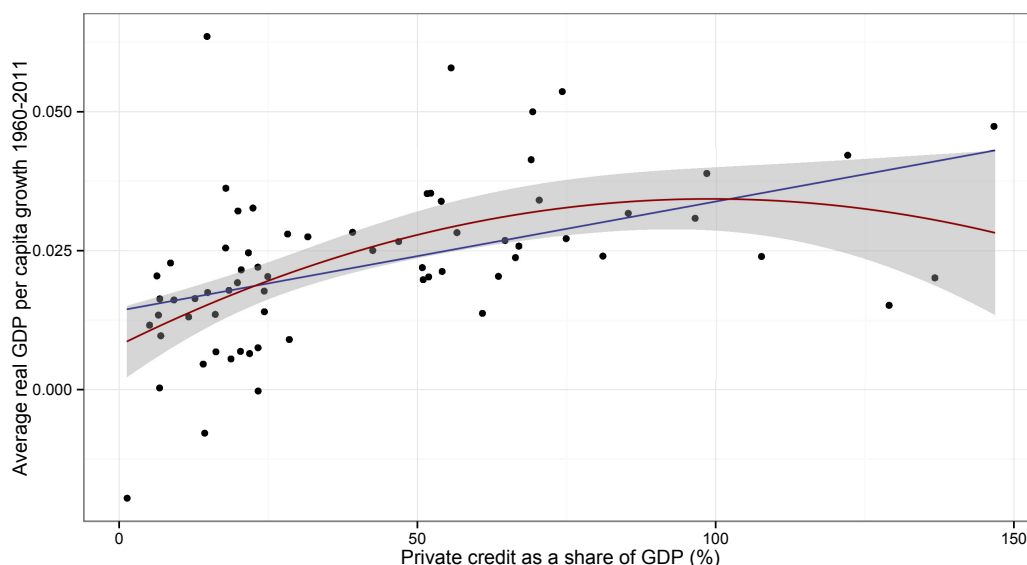
market characteristics exhibit the highest PIPs. These findings are broadly in accord with the specification from Fernandez et al. (2001) despite the choice of an alternative parameter prior and the consideration of an extended period.

Although private credit ranks near the middle of the list of explanatory variables and its mean value of the coefficient is positive, the PIP is only 7%. This result indicates that credit is unlikely included as the explanatory variable in the "true" growth model. Overall, we find very limited support for the notion that financial depth is important for long-term economic growth.

In the baseline estimation, we follow Fernandez et al. (2001) and use a uniform model prior. However, we depart from that study in the selection of the parameter prior. Instead of using the BRIC prior, we employ the hyper-g prior, as the literature now considers it superior. The essential disadvantage of employing the BRIC prior is documented by Feldkircher and Zeugner (2009). They describe a phenomenon of a "supermodel effect", arguing that with a high fixed prior g, the shrinkage-factor $\frac{g}{1+g}$ in equation 2.14 increases, thus increasing the size penalty, and may skew the posterior model distribution to smaller models. This choice of a large g under fixed priors can result in a preference for overly simplistic models. According to Feldkircher and Zeugner (2009), the phenomenon is characteristic of BMA applications to growth regressions with numerous covariates. They further claim that using a model-specific hyper-g prior leads to more robust estimates. This is why we abstain from employing the BRIC prior and focus on alternative options for parameter priors in our

Table 2.2: Private credit and growth, baseline results
Bayesian model averaging

	PIP	Post Mean	Post SD
Life expectancy	1.00	0.00078	0.00023
GDP level in 1960	1.00	-0.01330	0.00234
Fraction GDP in mining	1.00	0.05972	0.01369
Fraction Confucian	1.00	0.04527	0.01146
Black market premium	1.00	-0.01040	0.00327
Exchange rate distortions	0.99	-0.00009	0.00003
Sub-Sahara dummy	0.99	-0.01377	0.00539
SD of black market premium	0.98	0.00003	0.00001
Equipment investment	0.97	0.11111	0.04474
Fraction Buddhist	0.84	0.00968	0.00653
Size of labor force	0.75	7.1e-08	6.4e-08
French colony dummy	0.64	0.00405	0.00402
Fraction Muslim	0.53	0.00445	0.00529
Fraction of pop. speaking English	0.48	-0.00335	0.00445
Non-equipment investment	0.38	0.01197	0.01942
Latin America dummy	0.28	-0.00152	0.00299
Rule of law	0.24	0.00169	0.00388
Fraction Hindu	0.16	-0.00349	0.01138
Ethnolinguistic fractionalization	0.16	0.00090	0.00268
Absolute latitude	0.13	0.00002	0.00005
Fraction speaking foreign language	0.11	0.00038	0.00144
Fraction Catholic	0.10	0.00041	0.00180
British colony dummy	0.09	0.00026	0.00133
Ratio of workers to population	0.08	0.00059	0.00295
Public education share	0.08	0.00754	0.03897
Private credit	**0.07**	**0.00025**	**0.00138**
Number of years of open economy	0.06	-0.00030	0.00179
Spanish colony dummy	0.06	-0.00016	0.00115
Fraction Jewish	0.05	0.00045	0.00319
Primary school enrollment	0.05	0.00027	0.00214
Fraction Protestant	0.04	-0.00006	0.00108
Degree of capitalism	0.04	0.00002	0.00018
Age	0.03	-5.5e-07	0.00001
Outward orientation	0.03	-0.00004	0.00043
High school enrollment	0.03	-0.00029	0.00572
Area	0.03	4.9e-09	9.7e-08
Revolutions and coups	0.03	-0.00005	0.00083
Civil liberties	0.03	-0.00001	0.00019
War dummy	0.03	-0.00001	0.00036
Primary exports	0.03	-0.00001	0.00083
Population growth	0.02	0.00032	0.02622
Political rights	0.02	-2.2e-06	0.00014

robustness checks.

The birth-death MC^3 sampler described in Subsection 2.4.7 is our preferred approach for approximating the PMP distribution. To ensure sufficient convergence of the sampler, we specify 15 million iterations with 3 million initial burn-ins. The full estimation diagnostics is available upon request. The average number of regressors included in the model is 19.09, and the correlation between analytical and sampler PMP stands at 0.56. We realize that this PMP correlation is far from ideal, but estimation with higher iteration counts and subsequently higher PMP correlation yields nearly identical results.[5] Note that below, we employ different parameters and model prior structures and achieve a PMP close to 1, while the PIPs remain largely unchanged.

Next, we examine whether the baseline results are robust to different parameter priors. Ciccone and Jarocinski (2010) posit that BMA results are sensitive to data revisions under certain prior structures. Eicher et al. (2011) find that the PIPs of some growth determinants depend on the chosen parameter prior. Therefore, we perform the estimation using UIP. We also check the robustness of the MC^3 sampler using the "reverse-jump" algorithm and the model prior by employing a random binomial model prior (see Zeugner (2011) for details).

The model comparison for different parameter priors and MC^3 algorithms is depicted in Figure 2.2. Model 1 includes the PIPs under our baseline specification. Model 2 employs the same priors but applies the "reverse-jump" MC^3 algorithm. Models 3 and 4 yield the results when we use UIP under the birth-death and reverse-jump samplers, respectively. Though employing the reverse-jump sampler only marginally alters the PIPs, switching to the UIP prior leads to slightly lower inclusion probabilities and model size. Overall, these findings indicate that our baseline results are robust.

The beta-binomial ("random") model prior offers meaningful insights. This setting allows for a less restrictive selection of model priors around the prior expected model size and limits the risk of imposing any particular one (Ley & Steel, 2009b). Thus, if the true model size is lower than that expected by the prior (21), we should expect the mean model size to decline in this setting. We present the results of the estimation using this model prior in Figure 2.5 in the Appendix. In the first setting with a hyper-g prior, the mean size declines to 15.05 and the PMP correlation between analytical and MC^3 sampler likelihood

---

[5]Specifically, we ran the estimation using 50 million iterations and 5 000 000 burn-ins to arrive at a PMP correlation of 0.82. Characteristics in terms of mean model size and PIPs remain virtually the same.

Figure 2.2: Model comparison with private credit
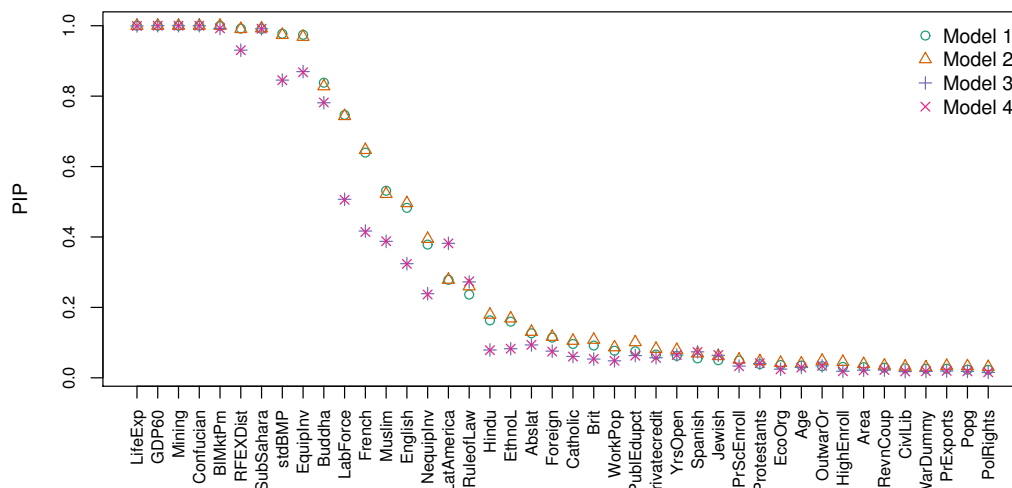
Note: Model 1=hyper-g,birth-death; Model 2=hyper-g,reverse-jump; Model 3=UIP,birth-death; Model 4=UIP,reverse-jump

achieves a satisfactory value of 0.96. The most important variables according to their PIPs remain nearly unchanged, although their relative positions adjust. One significant change is the decline in the PIP of the volatility of the black market premium to 14%. Finally, the inclusion probability of private credit increases marginally to 9%.

We also limit the period under consideration to 1960-1990 and examine whether the effect of financial development is stronger for this time period, as suggested by Rousseau and Wachtel (2011). We find that none of these modifications substantially affects our primary results concerning the relationship between private credit and economic growth. The PIP of private credit estimated on the subsample before 1990 does not appear to differ from that obtained for the full period up to 2011. As a robustness check of our results, we also use the values of private credit from the beginning of the observed period instead of the averages, but we find that the coding change has a negligible effect. These results are available upon request.

2.5.2   New Financial Development Indicators

We examine the effect of new financial indicators on long-term growth in this subsection. Specifically, we additionally include the following variables in our estimation: bank Z-score, net interest margin, stock market turnover, and

stock market capitalization. Čihák et al. (2013) identify these as proxies for different aspects of the financial sector. Specifically, they propose using bank Z-score to assess the stability of the banking sector, the net interest margin to proxy for the efficiency of the banking sector, stock market turnover as a proxy for the efficiency of the stock market, and stock market capitalization to measure the depth of stock markets. These measures, particularly the first two, are rarely used in growth regressions (Berger et al. (2004) and Hasan et al. (2009) being the exceptions), despite the fact that they might better depict the relationships outlined by theory than traditionally employed variables. As we discuss in Section 2.3, the main issue lies in their availability. However, the GFDD provides a significant improvement in this regard, and many series are available since the late 1980s. In addition, we retain domestic credit to the private sector among the covariates to account for the overall size of the banking sector. Given the data limitations, our sample is reduced to 60 countries. For eight countries from our original sample used for private credit, at least one value of the new financial indicators is missing.

Figure 2.3 provides an initial examination of the interaction between individual financial indicators and economic growth. First, we observe a distinct inverse relationship between the net interest margin and economic growth. Second, bank Z-score and growth display only a marginally positive relationship. Third, market capitalization and market turnover appear to be positively related to growth, which is in line with Levine and Zervos (1998). In addition, Table 2.3 provides the correlations among the financial indicators. The correlations are typically far from one, thus providing additional impetus to examine further measures of financial development in the growth regressions. In addition, we present the jointness statistics in the Appendix 2.B.

Table 2.3: Correlation matrix of new financial indicators

Net interest margin	1.00				
Bank Z-score	-0.14	1.00			
Private credit	-0.71	0.03	1.00		
Market capitalization	-0.44	0.08	0.71	1.00	
Market turnover	-0.54	0.02	0.47	0.33	1.00

We report the results of the estimation in a similar fashion as we did for private credit. We retain the baseline specification with the hyper-g parameter prior, uniform model prior, and birth-death MC^3 sampler. The number of iterations remains at 15 million, and we specify 3 million burn-ins. The full

Figure 2.3: Financial indicators and growth
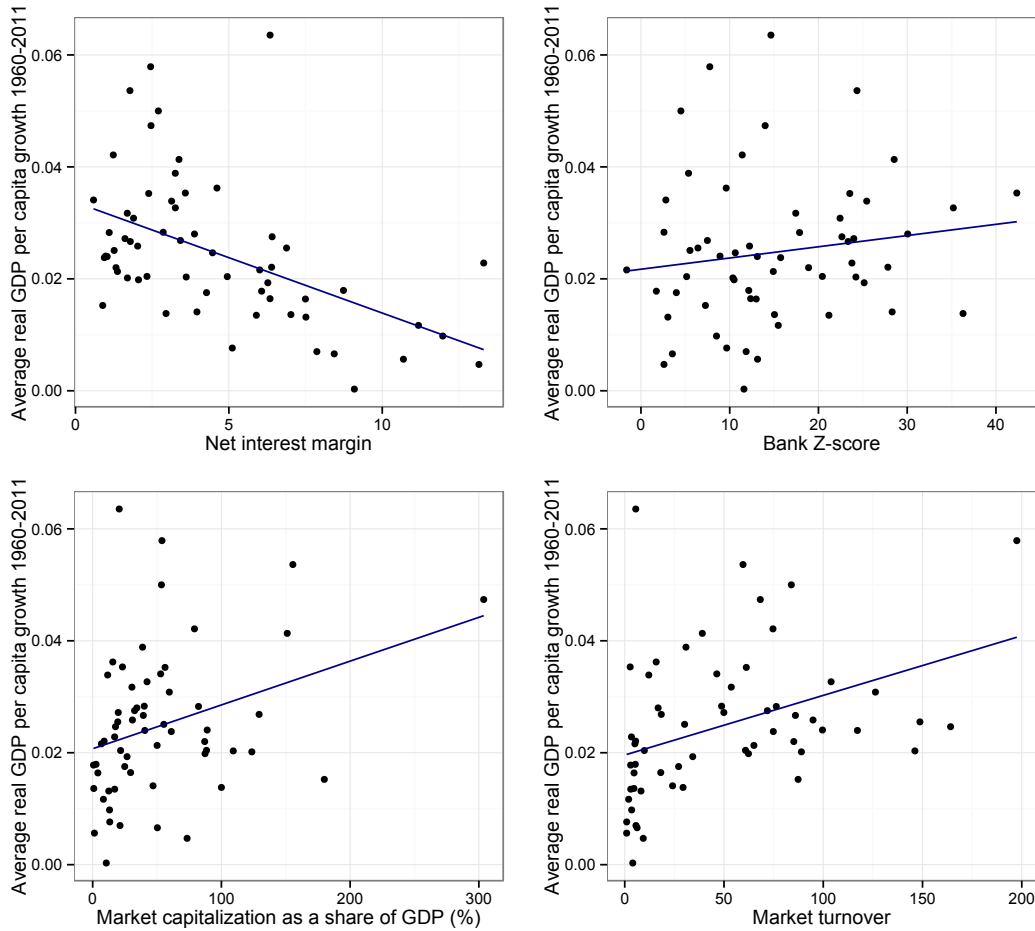
estimation diagnostics is available upon request. As in the previous subsection, running more iterations does not affect the resulting PIPs and posterior means, although it leads to a higher convergence of the sampler. We primarily focus on the interpretation of the results concerning financial indicators, as the other explanatory variables' PIPs remain broadly similar to those of specification for private credit.

We present the posterior statistics of the explanatory variables in Table 2.4. Interestingly, the variable proxying for bank efficiency exhibits a comparatively higher PIP than that reflecting its depth. Net interest margin ranks high among the explanatory variables with a 97% inclusion probability. The posterior mean of the coefficient is negative, in accordance with our expectations. A lower interest margin stems from a smaller discrepancy between banks' borrowing and lending rates. Thus, if banks are able to channel resources at a lower margin, this appears to positively affect long-term economic growth (Rousseau,

Table 2.4: New financial indicators and growth 1960-2011, baseline results

	PIP	Post Mean	Post SD
GDP level in 1960	1.00	-0.01075	0.00234
Fraction GDP in mining	1.00	0.04669	0.01338
Exchange rate distortions	1.00	-0.00009	0.00003
Fraction Confucian	1.00	0.03896	0.01093
Life expectancy	1.00	0.00057	0.00019
Fraction Buddhist	0.98	0.01255	0.00497
Net interest margin	**0.97**	**-0.00115**	**0.00045**
Equipment investment	0.85	0.07432	0.04648
Fraction Protestant	0.33	-0.00225	0.00402
Ratio of workers to population	0.33	0.00382	0.00671
Bank Z-score	**0.25**	**0.00004**	**0.00009**
French colony dummy	0.24	0.00183	0.00411
SD of black market premium	0.22	3.1e-06	0.00001
Rule of law	0.19	0.00139	0.00363
Outward orientation	0.19	-0.00050	0.00133
Market turnover	**0.17**	**0.00001**	**0.00002**
Size of labor force	0.12	6.6e-09	2.6e-08
Spanish colony dummy	0.12	0.00054	0.00192
Fraction of pop. speaking English	0.11	-0.00044	0.00168
Fraction Jewish	0.08	0.00093	0.00423
Fraction Muslim	0.08	0.00033	0.00158
Private credit	**0.07**	**0.00028**	**0.00145**
Fraction Catholic	0.07	-0.00025	0.00139
Primary exports	0.06	0.00020	0.00135
Absolute latitude	0.05	4.2e-06	0.00003
Fraction Hindu	0.05	-0.00048	0.00435
Fraction speaking foreign language	0.05	0.00009	0.00068
Population growth	0.04	-0.00554	0.04705
Number of years of open economy	0.04	0.00011	0.00093
Age	0.04	-6.6e-07	0.00001
War dummy	0.04	-0.00005	0.00047
High school enrollment	0.04	-0.00061	0.00575
Latin America dummy	0.04	-0.00006	0.00079
Black market premium	0.04	0.00010	0.00101
Non-equipment investment	0.04	-0.00040	0.00408
Political rights	0.04	0.00002	0.00018
British colony dummy	0.04	-0.00001	0.00045
Area	0.03	7.9e-09	8.9e-08
Degree of capitalism	0.03	0.00002	0.00019
Public education share	0.03	0.00078	0.01915
Revolutions and coups	0.03	-0.00005	0.00076
Sub-Sahara dummy	0.03	-0.00001	0.00087
Primary school enrollment	0.03	-0.00007	0.00129
Ethnolinguistic fractionalization	0.03	-0.00001	0.00064
Market capitalization	**0.02**	**1.1e-07**	**3.3e-06**
Civil liberties	0.02	0.00001	0.00016

1998). Additionally, the posterior mean of bank Z-score is positive, implying that stable banking systems are beneficial for economic growth, although the PIP at 25% does not offer much confidence that the Z-score is a crucial determinant of long-term growth. Stock market turnover is also accorded little importance, with a PIP of 17%. The positive sign of the mean is in line with our expectations regarding an efficient resource allocation being beneficial for growth. Moreover, it supports the conclusion of Levine and Zervos (1998) that an active stock market contributes to economic growth. However, we wish to note that this indicator might not coherently capture the efficiency of the markets. A high turnover ratio could reflect low friction in trading and the spread of information (Levine, 2005). On the other hand, other research finds that more trading does not necessarily prevent asset price misalignments and its corrections (Brunnermeier & Nagel, 2004). Strikingly, the measures capturing the depth of both the banking sector and stock markets exhibit very small PIPs. Overall, our results indicate that the approach used to measure financial development is crucial in determining the estimated effect of finance on growth.

To provide robustness checks, we again perform the estimation with alternative priors.[6] Figure 2.4 illustrates the comparison. The implications of different priors are similar to those experienced in the estimation regarding private credit. The UIP parameter prior subtly alters the PIP of the covariates without having a major effect on the interpretation. Providing greater flexibility in selecting model size by assuming a random model prior reduces the posterior mean model size and the PIP of several variables, but the set of top-ranked regressors remains largely unchanged. The relative importance of financial indicators changes to some extent. Net interest margin remains among the most important variables with an 86% PIP. All the remaining indicators exhibit low PIP below 10%. This is due to the smaller size induced by the random model prior. The results using dilution prior which accounts for correlation among covariates decreases the PIP of nearly all variables. However, the importance of net interest margin still remains high with the PIP at 87%.

Our baseline estimations suggest that bank efficiency is crucial for growth. We perform an additional estimation to check the robustness of this finding. and estimate BMA with lagged covariates. For reasons of data availability, we use real growth in GDP per capita over the period 2000–2011 and take the values of the financial indicators in the year 2000. The advantage of this

---

[6]We also perform estimations using an alternative MC^3 sampler, but the differences in posterior statistics are marginal.

Table 2.5: New financial indicators and growth 2000-2011, baseline results

	PIP	Post Mean	Post SD
Exchange rate distortions	1.00	0.00022	0.00004
War dummy	1.00	0.01149	0.00290
Net interest margin	**1.00**	**-0.00212**	**0.00055**
Primary exports	1.00	0.01699	0.00496
Fraction Confucian	1.00	0.04151	0.01130
Non-equipment investment	1.00	-0.09469	0.02661
Political rights	1.00	0.00641	0.00152
Latin America dummy	1.00	0.01679	0.00470
Fraction GDP in mining	1.00	0.08843	0.01789
Ratio of workers to population	1.00	0.04116	0.00919
Revolutions and coups	1.00	-0.03279	0.00649
Outward orientation	1.00	0.00900	0.00261
Sub-Sahara dummy	1.00	-0.03589	0.00910
Fraction Hindu	0.94	0.03725	0.01387
SD of black market premium	0.88	0.00003	0.00002
Private credit	**0.53**	**-0.00003**	**0.00004**
Life expectancy	0.31	0.00011	0.00021
High school enrolment	0.25	-0.00932	0.02257
Bank Z-score	**0.21**	**-0.00004**	**0.00010**
Rule of law	0.16	0.00106	0.00369
French colony dummy	0.15	-0.00091	0.00311
Degree of capitalism	0.14	0.00014	0.00055
Size of labour force	0.13	1.3e-08	5.0e-08
Black market premium	0.12	0.00084	0.00375
Spanish colony dummy	0.11	-0.00046	0.00250
Civil liberties	0.10	-0.00018	0.00096
Number of years of open economy	0.09	0.00034	0.00206
Age	0.09	1.1e-06	0.00001
GDP level in 2000	0.09	0.00009	0.00076
British colony dummy	0.08	0.00004	0.00079
Public education share	0.08	0.00470	0.03815
Absolute latitude	0.08	4.3e-06	0.00003
Fraction Muslim	0.08	0.00035	0.00215
Population growth	0.08	-0.00603	0.07020
Market capitalization	**0.07**	**3.8e-07**	**4.7e-06**
Fraction Buddhist	0.07	-0.00021	0.00167
Fraction Catholic	0.07	-0.00012	0.00102
Ethnolinguistic fractionalization	0.07	0.00028	0.00171
Primary school enrolment	0.07	0.00026	0.00278
Market turnover	**0.07**	**4.5e-07**	**3.7e-06**
Fraction Jewish	0.07	0.00017	0.00230
Area	0.07	1.3e-08	1.3e-07
Fraction speaking foreign language	0.07	0.00011	0.00089
Fraction Protestants	0.06	0.00007	0.00107
Fraction of pop. speaking English	0.05	-0.00011	0.00103
Equipment investment	0.04	0.00026	0.00815

Figure 2.4: Model comparison with all financial indicators 1960-2011
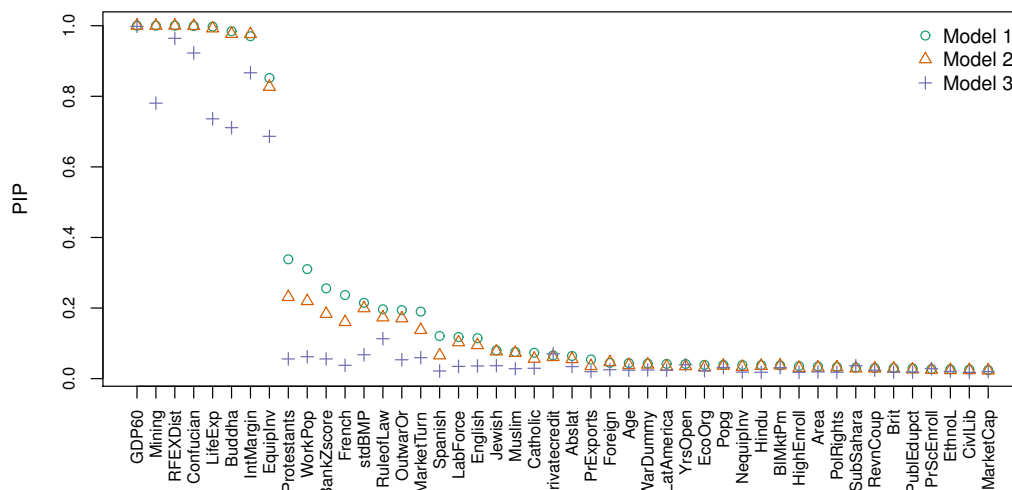
Note: Parameter and model prior comparison. Model 1=hyper-g, uniform model prior; Model 2=UIP, uniform model prior, Model 3=hyper-g, dilution model prior

approach is that we examine how past values of financial indicators influence current growth. Clearly, the disadvantage is that the time coverage for the dependent variable is restricted to just over a decade.[7] Implicitly, this may also be regarded as robustness check of the sensitivity of our results to the variable coding. We present the results in Table 2.5. Interestingly, the results remain largely unchanged. Net interest margin remains among the covariates with the highest PIP. The posterior mean of the coefficient is negative. The PIP of private credit is 49%, but the mean is negative. We hypothesize that the negative mean is a consequence of our sample period including the current global financial crisis, which has been characterized by deleveraging in many developed countries. The PIP of the other financial indicators is not high.

2.5.3   Non–linearities in Finance and Growth Nexus

Finally, we examine the possibility of a nonlinear relationship between financial indicators and growth. Several recent studies on financial development and economic growth devote substantial attention to nonlinearities in the relation-

---

[7]Alternatively, we also estimate 2SLS–BMA regressions following the methodology of Durlauf et al. (2008), which consists of two steps. We regress the endogenous financial indicators on our set of instruments in the first stage. The fitted values of financial indicators enter into the second stage BMA estimation. The results are largely in line with our baseline results and are available from the authors upon request.

ship between financial development and economic growth (see, for example, Cecchetti and Kharroubi (2012), Law and Singh (2014)). In addition, we also examine several possible interaction effects in finance–growth nexus such as whether private credit is conducive to growth only when financial system is stable.

When considering the quadratic and interaction terms, we rely on the strong heredity principle to adjust prior model probabilities. This approach has been suggested in the literature to ensure appropriate interpretation of the results. In essence, the quadratic and interaction terms may only be evaluated when their linear counterparts are included in the model. Therefore, they cannot mask potential effects of linear terms.

The results of the specification focused only on private credit do not alter our conclusions from the basic linear setup. The posterior inclusion probabilities of private credit and its quadratic term are 8% and 1%, respectively.[8] Next, we present the results with all financial indicators in Table 2.6. The PIPs on the linear terms are similar to the ones in the baseline linear specification from the previous subsection. The PIP on the net interest margin remains high at 88%. At the same time, we find very low posterior inclusion probabilities for all the quadratic terms with the exception of the net interest margin, which stands at 38%. While this value is not higher than sometimes suggested cut-off threshold of 50%, it provides some weak evidence for decreasing marginal returns of our efficiency indicator.

Table 2.6: New financial indicators and quadratic terms Bayesian model averaging

	PIP	Post Mean	Post SD
Net interest margin	0.88	-0.00192	0.00155
Net interest margin sq.	0.38	0.00006	0.00010
Market turnover	0.20	0.00003	0.00009
Bank Z-score	0.19	0.00003	0.00009
Market turnover sq.	0.12	-1.3e-07	4.0e-07
Private credit	0.09	0.00001	0.00005
Private credit sq.	0.03	-4.4e-08	2.7e-07
Market capitalization	0.01	-2.1e-07	4.7e-06
Bank Z-score sq.	0.01	1.3e-07	1.4e-06
Market capitalization sq.	0.00	6.6e-10	1.7e-08

---

[8]In this subsection we report only the posterior statistics of the financial variables. The full results including the other variables are available upon request.

Table 2.7: New financial indicators and interaction terms
Bayesian model averaging

	PIP	Post Mean	Post SD
Net interest margin	0.95	-0.00110	0.00050
Bank Z-score	0.29	0.00005	0.00010
Market turnover	0.18	0.00001	0.00002
Private credit	0.08	2.8e-06	0.00002
Market capitalization	0.03	2.1e-07	4.8e-06
Bank Z-score*Net interest margin	0.02	5.8e-07	5.9e-06
Net interest margin*Private credit	0.00	3.8e-08	1.4e-06
Bank Z-score*Private credit	0.00	-5.4e-10	6.9e-08

Finally, we report the results on the interaction terms. In the estimation we take the baseline scenario with all financial indicators and augment it with the interactions between private credit (depth), bank Z-score (stability), and net interest margin (efficiency). Table 2.7 summarizes the results. While the PIPs for the linear terms of financial indicators remain largely unchanged, the PIPs for the examined interaction terms are close to zero.

2.6 Conclusions

We contribute to the voluminous finance and economic growth literature in two ways. First, we use Bayesian model averaging (Raftery et al., 1997). This methodology is firmly grounded in statistical theory and allows the researcher to jointly evaluate a large number of potential covariates considered in the literature. This is important because we know that regression model uncertainty in growth regressions is high (Durlauf et al., 2008; Sala-I-Martin et al., 2004) and there are numerous potential determinants of growth that could be included. Without considering model uncertainty, researchers examining the finance-growth nexus risk omitted variable bias and inconsistently estimated parameters.

Second, the previous literature examining the finance-growth nexus largely employs measures of financial depth (for both the banking sector and stock markets) but rarely examines measures of the efficiency of financial intermediaries or financial stability. For this reason, we use newly developed financial indicators from the World Bank's GFDD. These indicators capture not only depth but also efficiency and stability. It is vital to revisit the finance and

growth literature because recent studies report that excessive financial development harms growth (Cecchetti & Kharroubi, 2012).

Using the updated well-known cross-country growth dataset by Fernandez et al. (2001), we find that traditional indicators of financial depth are not robustly related to long-term economic growth. The measures of financial depth and financial stability exhibit posterior inclusion probabilities well below 50%. However, our results suggest that bank efficiency, as proxied by the net interest margin, is crucial for long-term growth. The corresponding posterior inclusion probability is on average around 90%. This result is in line with theory, which indicates that the financial sector is essential in channeling resources from savers to borrowers Pagano (1993). These results are robust to different parameter and model priors in Bayesian model averaging. The results are also robust once we address the endogeneity of financial indicators. In addition, we do not find non–linearities and various interaction effects (such as the effect of the interaction of credit and financial stability) important for finance–growth nexus.

Overall, we find that the measurement of financial development is crucial in determining the estimated effect of finance on growth. Based on our global sample, the results attribute a greater role to the banking sector and its efficiency in fostering economic growth. Therefore, our results suggest that the quality of financial intermediation rather than the quantity of finance matters for growth. Our results thus stand in contrast to the recent papers suggesting that too much finance harms growth. We show that once we distinguish between quality and quantity of finance, we find that quality matters and quantity is largely irrelevant for long–term real growth. In terms of policy implications, our results indicate that the current wave of regulatory changes intended to safeguard financial stability should carefully analyze the consequences for the efficiency of financial intermediaries.

References

Acemoglu, D., Johnson, S., & Robinson, J. (2001). Colonial origin of comparative development: An empirical investigation. *American Economic Review*, *91*, 1369–1401.

Ang, J. B. (2008). A survey of recent developments in the literature of finance and growth. *Journal of Economic Surveys*, *22*, 536–576.

Ang, J. B. (2013). Are modern financial systems shaped by state antiquity? *Journal of Banking & Finance*, *37*(11), 4038–4058.

Ang, J. B., & Kumar, S. (2014). Financial development and barriers to the cross-border diffusion of financial innovation. *Journal of Banking & Finance*, *39*(100), 43–56.

Arcand, J., Berkes, E., & Panizza, U. (2015). Too much finance? *Journal of Economic Growth*, *20*(2), 105–148.

Atje, R., & Jovanovic, B. (1993). Stock markets and development. *European Economic Review*, *37*, 632–640.

Barro, R. J. (1996). *Determinants of economic growth: A cross-country empirical study* (Working Paper 5698). National Bureau of Economic Research.

Barro, R. J., & Sala-i-Martin, X. (1992). Convergence. *Journal of Political Economy*, *100*(2), 223–251.

Beck, T., Demirgüç-Kunt, A., & Maksimovic, V. (2005). Financial and legal constraints to growth: Does firm size matter? *The Journal of Finance*, *60*, 137–177.

Beck, T., Rioja, F. K., Valev, N. T., & Buyukkarabacak, B. (2012). Who gets the credit? and does it matter? households vs. firm lending across countries. *The B.E. Journal of Macroeconomics*, *12*(1), 1–46.

Berger, A., Hasan, I., & Klapper, L. (2004). Further evidence on the link between finance and growth: An international analysis of community banking and economic performance. *Journal of Financial Services Research*, *25*(2), 169–202.

Bolton, P., Santos, T., & Scheinkman, J. (2011). *Cream skimming in financial markets* (Working Paper No. 16804). National Bureau of Economic Research.

Brunnermeier, M. K., & Nagel, S. (2004). Hedge funds and the technology bubble. *Journal of Finance*, *59*(5), 2013–2040.

Cecchetti, S. G., & Kharroubi, E. (2012). *Reassessing the impact of finance on growth* (Working paper No. 381). Bank for International Settlements.

Cecchetti, S. G., & Kharroubi, E. (2013). *Why does financial sector growth crowd out real economic growth?* (Tech. rep.). Bank for International Settlements.

Cetorelli, N., & Strahan, P. E. (2006). Finance as a barrier to entry: Bank competition and industry structure in local U.S. markets. *Journal of Finance*, *61*(1), 437–461.

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

Christopoulos, D. K., & Tsionas, E. G. (2004). Financial development and economic growth: Evidence from panel unit root and cointegration tests. *Journal of Development Economics*, *73*(1), 55–74.

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

Čihák, M., Demirgüç-Kunt, A., Feyen, E., & Levine, R. (2013). *Financial development in 205 economies, 1960 to 2010* (Working Paper No. 18946). National Bureau of Economic Research.

Claessens, S., & Laeven, L. (2005). Financial dependence, banking sector competition, and economic growth. *Journal of the European Economic Association*, *3*, 179–207.

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

Doppelhofer, G., & Weeks, M. (2009). Jointness of growth determinants. *Journal of Applied Econometrics*, *24*, 209–244.

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

Eicher, T. S., Papageorgiou, C., & Raftery, A. E. (2011). Default priors and predictive performance in bayesian model averaging, with application to growth determinants. *Journal of Applied Econometrics*, *26*, 30–55.

Feldkircher, M., & Zeugner, S. (2009). *Benchmark priors revisited: On adaptive shrinkage and the supermodel effect in bayesian model averaging* (Working Paper No. 09/202). International Monetary Fund.

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

Fink, G., Haiss, P., & Hristoforova, S. (2003). *Bond markets and economic growth* (Working Paper No. 49). IEF.

Gallup, J. L., Sachs, J. D., & Mellinger, A. D. (1999). Geography and economic development. *International Regional Science Review*, *22*(2), 179–232.

Garretsen, H., Lensink, R., & Sterken, E. (2004). Growth, financial development, societal norms and legal institutions. *Journal of International Financial Markets, Institutions and Money*, *14*(2), 165–183.

George, E. I. (2010). Dilution priors: Compensating for model space redundancy. In *Borrowing strength: Theory powering applications–a festschrift for Lawrence D. Brown* (pp. 158–165). Institute of Mathematical Statistics.

Haggard, S., & Tiede, L. (2011). The rule of law and economic growth: Where are we? *World Development*, *39*(5), 673–685.

Hall, R. E., & Jones, C. I. (1999). Why do some countries produce so much more output per worker than others? *The Quarterly Journal of Economics*, *114*(1), 83–116.

Hasan, I., Koetter, M., & Wedow, M. (2009). Regional growth and finance in Europe: Is there a quality effect of bank efficiency? *Journal of Banking & Finance*, *33*(8), 1446–1453.

Jayaratne, J., & Strahan, P. E. (1996). The finance-growth nexus: Evidence from bank branch deregulation. *The Quarterly Journal of Economics*, *111*(3), 639–70.

Kindelberger, C. P. (1978). *Manias, panics and crashes.* New York, Basic Books.

King, R. G., & Levine, R. (1993). Finance, entrepreneurship and growth: Schumpeter might be right. *Quarterly Journal of Economics*, *108*, 717–737.

Kneer, C. (2013). *Finance as a magnet for the best and brightest: Implications for the real economy* (Working Paper No. 392). De Nederlandsche Bank.

Koetter, M., & Wedow, M. (2010). Finance and growth in a bank-based economy: Is it quantity or quality that matters? *Journal of International Money and Finance*, *29*(8), 1529–1545.

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

Law, S. H., & Singh, N. (2014). Does too much finance harm economic growth? *Journal of Banking & Finance*, *41*, 36–44.

Levine, R. (2005). Finance and growth: Theory and evidence. In P. Aghion & S. Durlauf (Eds.), *Handbook of economic growth* (pp. 865–934). Amsterdam, Elsevier.

Levine, R., & Zervos, S. (1998). Stock markets, banks, and economic growth. *American Economic Review*, *88*(3), 537–558.

Ley, E., & Steel, M. F. (2007). Jointness in bayesian variable selection with applications to growth regression. *Journal of Macroeconomics*, *29*, 474–493.

Ley, E., & Steel, M. F. (2009a). Comments on 'Jointness of growth determinants'. *Journal of Applied Econometrics*, *24*, 248–251.

Ley, E., & Steel, M. F. (2009b). On the effects of prior assumptions in bayesian model averaging with application to growth regression. *Journal of Applied Econometrics*, *24*, 651–674.

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

Long, J. B. D., & Summers, L. (1991). Equipment investment and economic growth. *Quarterly Journal of Economics*, *106*(2), 445–502.

Minsky, H. (1991). The risk of economic crisis. In M. Feldstein (Ed.). Chicago, University of Chicago Press.

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

Pagano, M. (1993). Financial markets and growth: An overview. *European Economic Review*, *37*(2 -3), 613–622.

Peia, O., & Roszbach, K. (2015). Finance and growth: Time series evidence on causality. *Journal of Financial Stability*, *18*, 105–118.

Petersen, M. A., & Rajan, R. G. (1997). Trade credit: Theories and evidence. *Review of Financial Studies*, *10*(3), 661–691.

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

Rajan, R. G., & Zingales, L. (1998). Financial dependence and growth. *American Economic Review*, *88*(3), 559–586.

Rousseau, P. L. (1998). The permanent effects of innovation on financial depth:: Theory and us historical evidence from unobservable components models. *Journal of Monetary Economics*, *42*(2), 387–425.

Rousseau, P. L., & Wachtel, P. (2011). What is happening to the impact of financial deepening on economic growth. *Economic Inquiry*, *49*, 276–288.

Sala-I-Martin, X., Doppelhofer, G., & Miller, R. I. (2004). Determinants of long-term growth: A Bayesian averaging of classical estimates (BACE) approach. *American Economic Review*, *94*(4), 813–835.

Stiglitz, J. E. (2000). Capital market liberalization, economic growth, and instability. *World Development*, *28*, 1075–1086.

Thumrongvit, P., Kim, Y., & Pyun, C. S. (2013). Linking the missing market: The effect of bond markets on economic growth. *International Review of Economics and Finance*, *27*, 529–541.

Tobin, J. (1984). *On the efficiency of financial system.* Lloyds Bank Review.

Valickova, P., Havranek, T., & Horvath, R. (2015). Financial development and economic growth: A meta-analysis. *Journal of Economic Surveys*, *29*(3), 506–526.

Yilmazkuday, H. (2011). Thresholds in the Finance-Growth Nexus: A Cross-Country Analysis. *World Bank Economic Review*, *25*(2), 278–295.

Zeugner, S. (2011). *Bayesian model averaging with bms.*

Appendix

2.A Description of the Dataset

We use a commonly employed dataset on the determinants of growth developed by Fernandez et al. (2001). The dataset contains 41 explanatory variables that are potentially important for growth in 72 countries. Here, we describe the variables that do not assess financial development. Financial indicators, which we add to this dataset, are described in the main text.

We update the dataset by incorporating economic growth from new Penn World Table (PWT), extending the time period considered from the former 1960-1992 to 1960-2011. Our dependent variable is the average growth of real output-based GDP per capita. The mean value of the growth rate across the dataset is 2.27% with a standard deviation of 1.45%. The regressors in the dataset comprise various measures of economic, political, geographic, demographic, social, and cultural factors. As many of the variables are endogenous with respect to growth, the data typically come from 1960 or before.

The economic variables primarily capture established factors from neoclassical growth theories. The initial level of GDP is included to capture conditional convergence, such that lower starting levels imply higher growth rates (Barro & Sala-i-Martin, 1992). Additionally, physical capital investment is considered, distinguishing between equipment investment (machinery) and non-equipment investment (other). This follows Long and Summers (1991), who find that the impact of the former is a stronger driver of long-term economic growth. Human capital enters through primary school enrollment, higher education enrollment and public education share from Barro (1996). Life expectancy is often assumed to capture human capital other than education; therefore, it is also included among the regressors. Exchange rate fluctuations, the black market premium, and the volatility of the black market premium account for the degree of economic uncertainty. Exchange rates can affect a country's foreign direct investments and net exports, subsequently influencing economic growth. The black market premium then reflects the surplus on the exchange rate over the official foreign exchange market. High discrepancy mirrors greater uncertainty, and in addition to high volatility, we expect it to decelerate growth. Moreover, a set of variables accounts for economic policies. Outward orientation based on an import-export structure reflects the potential impact of international competition on domestic production efficiency. Economic organization

captures the degree of capitalism, using the classification developed by Hall and Jones (1999). The characteristic is measured on a six-degree scale ranging from "statist" to "capitalist" that depends on how much control the national government exerts over the economy. Finally, the degree of openness enters through the length of period that the country has experienced an open economy. All policy variables are assumed to be positively correlated with economic growth.

Geographic controls include dummy variables for Sub Saharan Africa, Latin America, total area, and absolute latitude. Spatial differences in economic growth have been established in the literature. The location of a country may influence growth through differences in transportation costs, disease burdens, or agricultural productivity (Gallup et al., 1999). A location farther from the equator should have a positive impact on growth.

The explanatory variables measuring political conditions within countries are colonial heritage, rule of law, indices for political rights, civil rights, and revolutions and coups. Political instability is further captured by war dummy, which equals 1 if the country suffered from war during 1960-1992. Acemoglu et al. (2001) note that colonial heritage is related to lower trust and malfunctioning institutions; therefore, former colonial status depresses growth. The rule of law is an established control in growth regressions, proxying for security, property rights, democratic government, and corruption (Haggard & Tiede, 2011). Civil liberties further accounts for the level of democracy and its relationship with income redistribution. If a large share of income is in the hands of a few, this may have consequences for economic agents' production incentives. Intuitively, revolutions and coups negatively affect growth by decreasing stability and infrastructure destruction.

The demographic characteristics of countries we use in our estimation are average age, religion, ethnolinguistic fractionalization, population growth, total labor force, ratio of workers in population, and language skills. Religion is found to be relevant to economic growth in Barro (1996). Population growth accounts for the neoclassical implication of a, ceteris paribus, decline in per capita growth with an increasing population. Language skills are approximated by the fraction of persons speaking English within a country and the fraction of persons speaking a foreign language. Hall and Jones (1999) demonstrate how better language skills are positively reflected in economic growth. They argue that this arises from facilitated internalization and the benefits of globalization. The full list of variable names and their abbreviations is presented below.

Additionally, PWT is missing observations on Algeria, Haiti, and Nicaragua.

Therefore, we have to drop them from the sample. Furthermore, the GFDD does not include data on Taiwan. Ultimately, we have 68 observations, encompassing both developed and developing countries. The list of countries is as follows: Argentina, Australia, Austria, Belgium, Bolivia, Brazil, Botswana, Canada, Chile, Cameroon, Congo (Brazzaville), Congo Dem. Rep (Kinshasa), Colombia, Costa Rica, Cyprus, Denmark, Dominican Republic, Ecuador, El Salvador, Ethiopia, Finland, France, United Kingdom, Germany, Ghana, Greece, Guatemala, Hong Kong, Honduras, India, Ireland, Israel, Italy, Jamaica, Jordan, Japan, Kenya, South Korea, Sri Lanka, Morocco, Madagascar, Mexico, Malawi, Malaysia, Nigeria, Netherlands, Norway, Pakistan, Panama, Peru, Philippines, Portugal, Paraguay, Senegal, Singapore, Spain, Sweden, Switzerland, Thailand, Tunisia, Turkey, Tanzania, Uganda, Uruguay, United States, Venezuela, Zambia, and Zimbabwe.

We use the following list of variables (the details on the construction of variables are available in Fernandez et al. (2001)): Absolute latitude, Age, Area, Black market premium, British colony dummy, Fraction Buddhist, Fraction Catholic, Civil liberties, Fraction Confucian, Degree of capitalism, Fraction of population speaking English, Equipment investment, Ethnolinguistic fractionalization, Fraction speaking foreign language, French colony dummy, GDP level in 1960, High school enrollment, Fraction Hindu, Fraction Jewish, Size of labor force, Latin America dummy, Life expectancy, Fraction GDP in mining, Fraction Muslim, Non-equipment investment, Outward orientation, Political rights, Population growth, Primary exports, Fraction Protestant, Primary school enrollment, Public education share, Revolutions and coups, Exchange rate distortions, Rule of law, Spanish colony dummy, SD of black market premium, Sub-Sahara dummy, War dummy, Ratio of workers to population, Number of years of open economy, Bank Z-score, Net interest margin, Stock market capitalization to GDP, Stock market turnover ratio, and Domestic credit to private sector.

2.B Jointness of financial indicators

To check the dependence between our financial variables, we compute the so–called jointness measure, which is based on the posterior distributions of explanatory variables over the model space. The goal of this exercise is to determine whether the different financial variables capture different sources of information in explaining the dependent variable (jointness) or if they represent

Figure 2.5: Model comparison with private credit
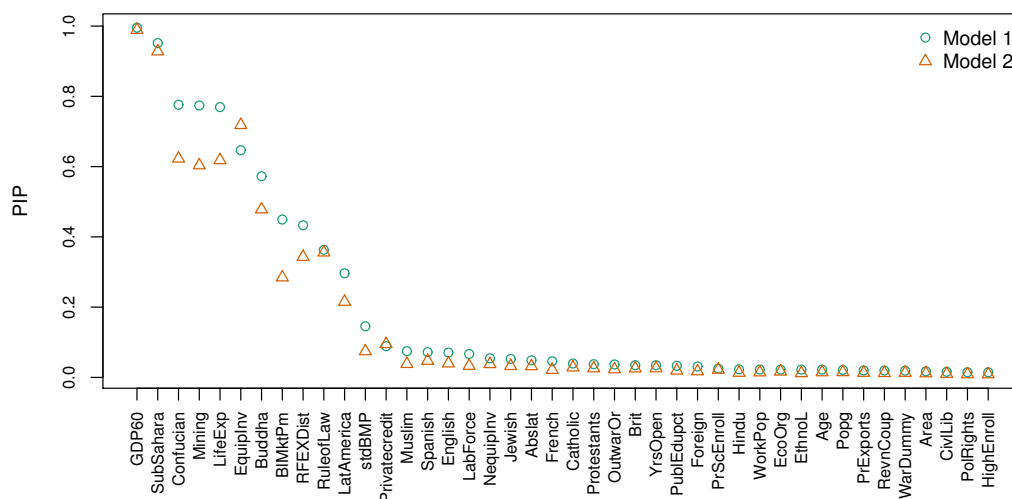
*Note: Model 1=hyper-g, random model prior; Model 2=UIP, random model
prior*

similar factors and should not be considered jointly in the model (disjointness)
(Ley & Steel, 2007).

Jointness statistics for our financial indicators are available in Tables 2.8–
2.10 with each table representing a different approach to jointness computation.
Tables 2.8 and 2.9 show that none of the numbers exceeds the threshold sug-
gested by Ley and Steel (2007) (LS) for decisive (dis)jointness. Nevertheless,
jointness statistics for some of the pairs suggest very strong jointness (e.g. mar-
ket capitalization and private credit). Another way of constructing jointness
statistic has been developed by Doppelhofer and Weeks (2009) (DW). Regard-
ing DW statistic, we find strong substitutability for private credit and net
interest margin. However, as has been stressed by Ley and Steel (2009a), DW
jointness statistic may become very sensitive and volatile if one of the variables
has high PIP and the other has a very low one. This is indeed the situation we
encounter in our analysis. In addition, if the net interest margin and private
credit were to be strong substitutes in a sense they would represent very sim-
ilar factors and thus be mutually replaceable in the estimation process, they
should also exhibit the same importance regarding economic growth if consid-
ered separately. These findings make us believe that the LS statistics are more
appropriate to judge the interdependence between financial indicators.

Table 2.8: Financial indicators, jointness statistics according to Ley and Steel (2007)

Net interest margin	.				
Bank Z-score	0.335	.			
Private credit	0.058	0.025	.		
Market capitalization	0.025	0.014	0.011	.	
Market turnover	0.224	0.158	0.041	0.027	.

Table 2.9: Financial indicators, jointness statistic according to Ley and Steel (2007), alternative

Net interest margin	.				
Bank Z-score	0.251	.			
Private credit	0.055	0.024	.		
Market capitalization	0.024	0.013	0.011	.	
Market turnover	0.183	0.136	0.039	0.027	.

Table 2.10: Financial indicators, jointness statistic according to Doppelhofer and Weeks (2009)

Net interest margin	.				
Bank Z-score	-0.372	.			
Private credit	**-2.373**	-1.025	.		
Market capitalization	0.028	-0.645	-0.521	.	
Market turnover	-0.829	0.165	-0.331	0.256	.

Chapter 3

Finance and Wealth Inequality

Abstract

Using a global sample, this paper investigates the determinants of
wealth inequality capturing various economic, financial, political,
institutional, and geographical indicators. Using instrumental vari-
able Bayesian model averaging, it reveals that only a handful of
indicators robustly matters 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 in-
equality.

3.1   Introduction

Wealth inequality differs markedly across countries (Davies et al., 2017; Davies et al., 2011; 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, 2019). 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., 2017; Davies et al., 2011; Piketty & Zucman, 2014; Saez & 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 & 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.

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,

---

[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, which can be interpreted as a measure of financial development.

we propose to employ 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 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 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 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 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.

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. Ac-

---

[4]BMA has been applied to 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).

cording 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 chapter is organized as follows. Section 3.2 reviews the literature on wealth inequality. Section 3.3 presents the data, and 3.4 introduces the BMA. We provide the results in Section 3.5 and conclude in Section 3.6. Additional robustness checks are available in the Appendix 3.A.

3.2   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

---

[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.

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 & 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 & 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 & Koreshkova, 2014), heterogeneity in rates of return (Benhabib et al., 2015; Lusardi et al., 2017), or entrepreneurship motives for saving (Cagetti & 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, 2019).

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 & 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 & Svejnar, 2015). One of the stylized facts is that the wealth distribution is much more concentrated than the income distribution. Figure 3.4 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 in-

vestment income method (jointly examining capital income and the net rate of return), and the *rich lists* assembled by various journals (Davies & 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. (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), Davies et al. (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.

3.3 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

---

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

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. (2017), Davies et al. (2011).[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 3.3.1.

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. It is difficult to rely on similar studies in the choice of regressors, since only a few papers on the same topic exist. To certain extent, we motivate the selection of our explanatory variables based on the studies investigating the determinants of income inequality and discussing the possible links between income inequality and wealth inequality (de Haan & Sturm, 2017; Roine & Waldenström, 2015). We 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 Table 3.18 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 Čihák 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 fi-

---

[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.

nancial 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.

Table 3.1 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 3.2 presents the descriptive statistics for the wealth inequality and

Table 3.1: 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, she imputes some of the indices. As an example, she approximates 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.

financial development indicators, whereas Table 3.3 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 3.2: 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 3.3: Finance and Wealth Inequality: Correlations

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

Note: FI - financial institutions, FM - financial markets.

3.3.1 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 about the wealth distribution. The OECD also systematically collects data regarding household wealth and its distribution since 2009. Information about the wealth share of

---

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

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 (2007), some contributions show there are no important differences in Sweden and the US (Kopczuk & Saez, 2004; Roine & Waldenström, 2009).

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

---

[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).

(31 countries), Davies et al. (2017) establish a relationship 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.

3.4 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. In what follows, we present the reasoning for the choices of our parameter and model priors as well as the reasoning how we address 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 (Ciccone & Jarocinski, 2010; Feldkircher & Zeugner, 2009; Liang et al., 2008).

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 3.9 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:

$$\beta_i|g \sim \ N(0, \sigma^2(g(X_i'X_i)^{-1}) \tag{3.1}$$

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 & 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 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

---

[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 $\frac{2}{a}$

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 with k_i regressors given θ is then

$$p(M_i) = \theta^{k_i}(1-\theta)^{K-k_i} \tag{3.2}$$

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:

$$p(M_i) = |R_i|\theta^{k_i}(1-\theta)^{K-k_i} \tag{3.3}$$

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 Factor (CBF) 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:

$$Y = X\beta + W\gamma + \epsilon \tag{3.4}$$

$$X = Z\delta + W\tau + \eta \tag{3.5}$$

where

$$\begin{pmatrix} \epsilon_i \\ \eta_i \end{pmatrix} \sim \mathcal{N}_2(0, \Sigma) \tag{3.6}$$

and

$$\Sigma = \begin{pmatrix} \sigma_{11} & \sigma_{12} \\ \sigma_{21} & \sigma_{22} \end{pmatrix}; \sigma_{12} = \sigma_{21} \neq 0 \tag{3.7}$$

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 MC^3 sampler presented in Appendix 3.H, 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 CBF, we refer to the original paper by Karl and Lenkoski (2012).

3.5   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, third, we present the results for restricted samples of high- / low- income countries, and fourth, we address endogeneity issues using IVBMA.

3.5.1   Baseline estimation

Figure 3.1 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 3.1 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 3.4 presents our BMA results regarding the determinants of wealth inequality. We present the explanatory variables sorted by their PIP values and interpret the results in accordance with Kass and Raftery (1995), who present a conventional rule of thumb to evaluate the PIP. When the PIP is lower than 50%, there is evidence against the effect, PIP between 50% and 75% suggest a weak evidence for the effect, PIP over 75%, but less than 95% means a 'positive' evidence for the effect, in case of PIP higher than 95%, but less than 99% there is strong evidence for the effect, and PIP over 99% provides decisive evidence for the effect.

According to our results, only a handful regressors robustly determines the cross-country variation in wealth inequality and exhibit PIPs greater than 0.5.

Figure 3.1: Finance and Wealth Inequality
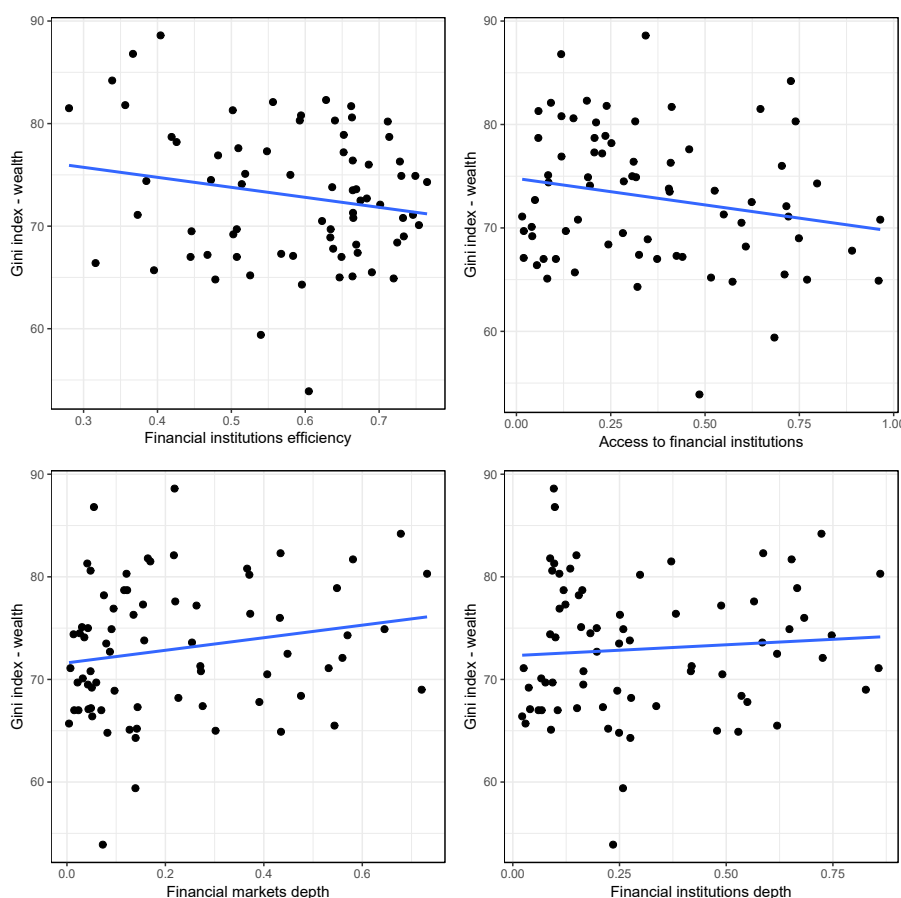
Note: Selected financial development indicators.

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 included in the mode with the highest PMP, we find the corresponding value of R-squared to be 0.57 (adjusted R-squared to be 0.52). This result suggests that we can explain approximately half of the variation in the cross-country differences in wealth inequality using only the eight most relevant regressors.[13] We discuss the effects of individual

---

[13]All regressors are statistically significant at the 1 or 10 percent level and exhibit signs of the coefficient estimates identical to those reported in Table 3.4. Alternatively, we estimate the model by OLS using the regressors with PIPs greater than 0.5 in the baseline BMA. The results again correspond to the BMA estimate. We report the output of both regressions in Table 3.17 in the Appendix.

regressors in detail below.

The variables with high PIPs 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 & Kharroubi, 2012; Law & 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 3.4, 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.

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.[14].

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, (Milanovic, 2016; Piketty, 2014) 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

---

[14]In one of the robustness checks, we also consider the relative redistribution (percentage reduction in market-income inequality due to taxes and transfers) Employing the alternative indicator of redistribution does not have any substantial impact on the other explanatory variables. The output of the estimation is available in Table 3.9.

inequality increases, but this effect is temporary, and later on, inequality falls slowly back to the steady state.

Table 3.4: 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)

Figure 3.2: Robustness Check: Different Prior Structure
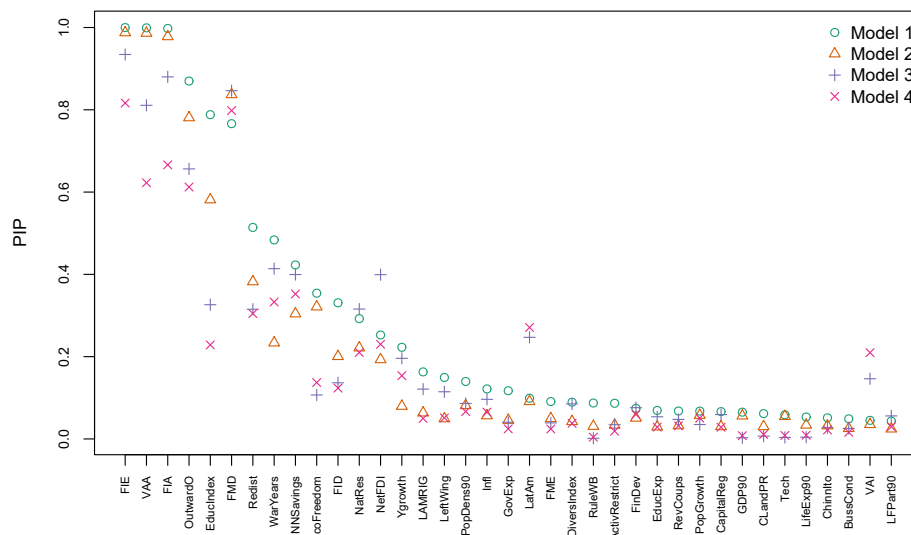
Note: Parameter and model prior comparison - compound indicators. Model 1: hyper-g, uniform; Model 2: UIP, uniform; Model 3: hyper-g, dilution; Model 4: UIP, dilution.

We report the baseline results, in which we employ the uniform model prior and hyper-g parameter prior, as described in Section 3.4. To provide robustness checks, we also use alternative parameter and model priors. Figure 3.2 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 overall 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.[15] None

---

[15]For example, we investigate cases where we drop groups of variables as defined in Table 3.12. Interestingly, when we drop a group of low PIP variables, the results are stable. On the other hand, if we drop a group which contains variables with high PIPs, the results deviate from the baseline estimates. This could be due to the introduction of omitted variable bias

of these additional regressors exhibited significant relevance in our model.[16]

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 3.4 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.

We present the results of overall effect of finance on wealth inequality in Figure 3.3. 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.[17]

3.5.2   High vs. low-income countries

We explore the non-linearity of the estimated effects by splitting our sample into two halves according to the level of GDP in 1990. Such an exercise, however, presents an issue for the estimation with the full set of explanatory variables as only 36 observations remain in each sample. To overcome this, we consider nine explanatory variables which occur in the top three models by their PMP which gives us enough degrees of freedom for the estimation.

We present the results in Table 3.5. The estimated coefficients of explanatory variables have their expected signs. We observe some heterogeneity in terms of PIPs. We find that technological advancement in agriculture (value added in agriculture) and openness of the economy (outward orientation) are dominant factors for low-income countries, while they are less relevant for the group of high-income countries. This is expected result given the prominence

---

in the latter case as dropping important regressors may severely affect coefficients on the remaining variables.

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

[17]Alternatively, we assessed the overall effect of finance on wealth inequality based on the estimation of the OLS model. We selected the explanatory variables that had PIP values in Table 3.4 greater than 0.5. The results are largely the same and are available upon request.

Figure 3.3: Effects of individual financial development components on inequality
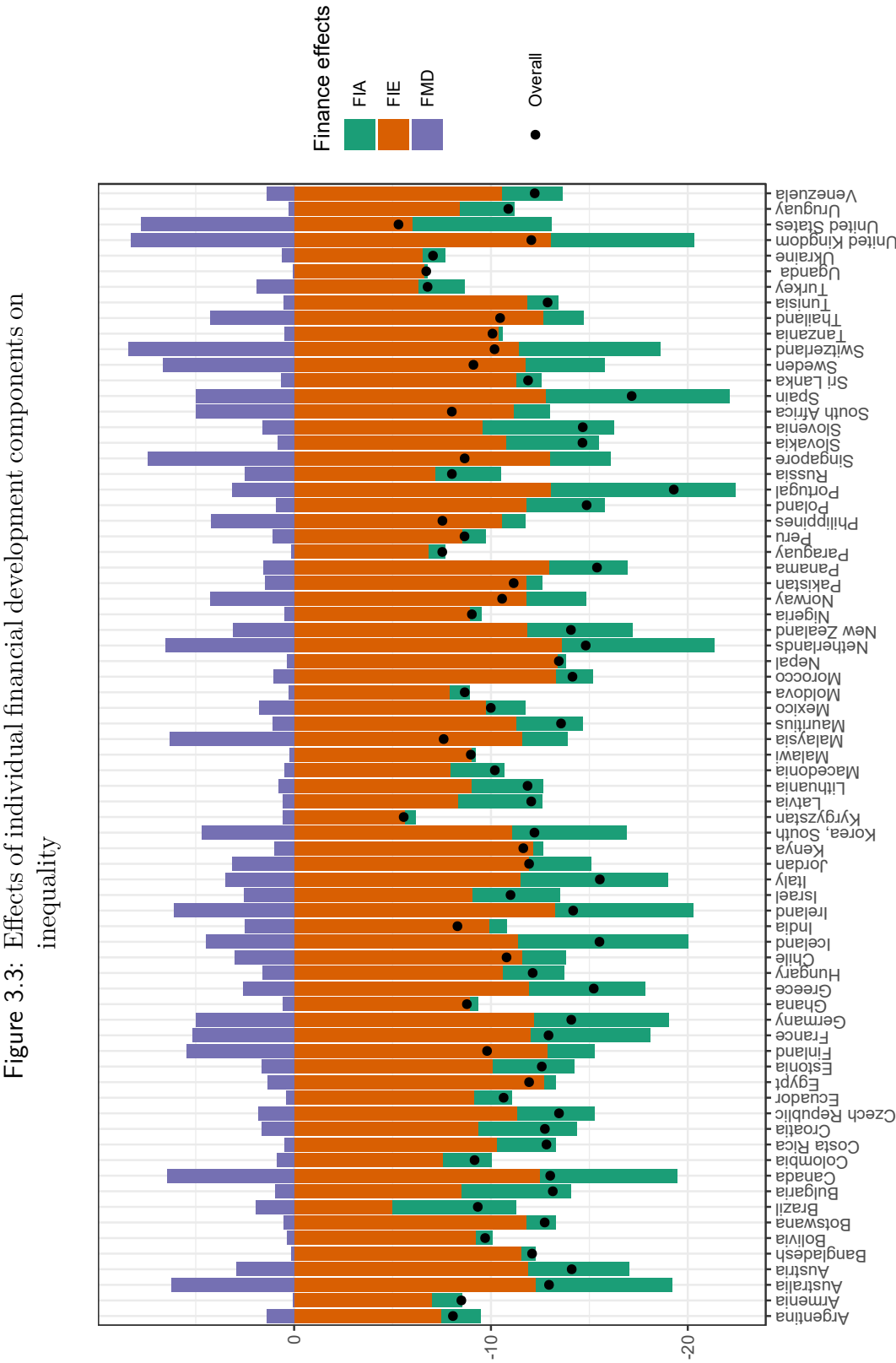
of agriculture sector in developing countries. Wars matter both for low-income and high-income countries. Regarding the financial variables, depth of the financial market increases wealth inequality both in low-income and high-income countries. Other financial variables (access to finance and efficiency of financial intermediaries) reduce wealth inequality especially in high-income countries. This suggests that the role of finance for wealth inequality rises with economic development.

Table 3.5: Estimates using the variables from the model with the highest posterior model probability and sample split into high- / low- income countries (based on GDP90)

	High-income		Low-income	
	PIP	Post. Mean	PIP	Post. Mean
Financial market depth	0.97	0.55171	0.66	0.21279
Average GDP growth	0.83	-0.31499	0.23	0.00877
Access to FI	0.76	-0.30279	0.27	0.04851
Number of war years	0.72	0.36526	0.62	0.09226
FI efficiency	0.60	-0.22569	0.24	-0.00668
Redistribution	0.56	-0.16593	0.27	-0.02704
Outward orientation	0.50	0.11034	1.00	0.36512
Education index (UN)	0.38	-0.10648	0.32	-0.04479
Value added in agriculture	0.29	0.03537	0.94	-0.33730

3.5.3 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 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.

We employ genetic distance from the United States (Spolaore & 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[18]. 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 genetic pattern in a particular country. Additionally, the components of our financial liberalization measure are exogenous to the wealth inequality as the change 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 instruments 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

---

[18]In our sample, the correlation is 0.06.

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 EFW measure turned out to be the strongest of the instruments. Our main IVBMA results rely on the just-identified case where we have two potential instruments for two potentially endogenous variables. We check the overidentification with Sargan test as introduced in Lenkoski et al. (2014), where the Sargan p-value is an weighted average of p-values from individual combinations of first and second stage models weighted by their model probabilities. The values are only available for potentially overidentified cases, where the number of instruments considered in the first stage is higher than the number of assumed endogenous variables. The averaged p-value from these cases confirms the validity of instruments.

Table 3.6 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 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 sampler. The latter approach tends to downweigh the PIP for the top and upweight it for the bottom regressors.[19] Overall, the IVBMA estimation largely supports our baseline findings.

3.6 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 & Zucman, 2014; Saez & 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 un-

---

[19]If we compare IVBMA output with the MC^3 PIPs from the baseline BMA, we obtain very similar values for both approaches.

Table 3.6: 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.

certainty. 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.

References

Abiad, A., Detragiache, E., & Tressel, T. (2010). A new database of financial reforms. *IMF Staff Papers*, *57*(2), 281–302.

Aiyagari, S. R. (1994). Uninsured idiosyncratic risk and aggregate saving. *The Quarterly Journal of Economics*, *109*(3), 659–684.

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

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

Arcand, J., Berkes, E., & Panizza, U. (2015). Too much finance? *Journal of Economic Growth*, *20*(2), 105–148.

Atkinson, A. B. (2007). Top incomes over the twentieth century: A contrast between continental european and english-speaking countries. In A. B. Atkinson & T. Piketty (Eds.). Oxford, Oxford University Press.

Avramov, D. (2002). Stock return predictability and model uncertainty. *Journal of Financial Economics*, *64*(3), 423–458.

Bagchi, S., & Svejnar, J. (2015). Does wealth inequality matter for growth? the effect of billionaire wealth, income distribution, and poverty. *Journal of Comparative Economics*, *43*(3), 505–530.

Beck, T., Demirgüç-Kunt, A., & Levine, R. (2007). Finance, inequality and the poor. *Journal of Economic Growth*, *12*(1), 27–49.

Benhabib, J., Bisin, A., & Zhu, S. (2015). The wealth distribution in bewley economies with capital income risk. *Journal of Economic Theory*, *159*, 489–515.

Bewley, T. (1977). The permanent income hypothesis: A theoretical formulation. *Journal of Economic Theory*, *16*(2), 252–292.

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

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

Bönke, T., Grabka, M., Schröder, C., & Wolff, E. N. (2017). *A head-to-head comparison of augmented wealth in germany and the united states* (Working Paper No. 23244). National Bureau of Economic Research.

Cagetti, M., & De Nardi, M. (2006). Entrepreneurship, frictions, and wealth. *Journal of Political Economy*, *114*(5), 835–870.

Castañeda, A., Díaz-Giménez, J., & Ríos-Rull, J.-V. (2003). Accounting for the u.s. earnings and wealth inequality. *Journal of Political Economy*, *111*(4), 818–857.

Cecchetti, S. G., & Kharroubi, E. (2012). *Reassessing the impact of finance on growth* (Working paper No. 381). Bank for International Settlements.

Christofides, C., Eicher, T. S., & Papageorgiou, C. (2016). Did established Early Warning Signals predict the 2008 crises? *European Economic Review*, *81*, 103–114.

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

Čihák, M., Demirgüç-Kunt, A., Feyen, E., & Levine, R. (2013). *Financial development in 205 economies, 1960 to 2010* (Working Paper No. 18946). National Bureau of Economic Research.

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

Comin, D., & Hobijn, B. (2010). An exploration of technology diffusion. *American Economic Review*, *100*(5), 2031–59.

Cremers, K. J. M. (2002). Stock return predictability: A bayesian model selection perspective. *The Review of Financial Studies*, *15*(4), 1223–1249.

Dabla-Norris, E., Kochhar, K., Suphaphiphat, N., Ricka, F., & Tsounta, E. (2015). *Causes and consequences of income inequality: A global perspective* (Staff Discussion Note No. 15/13). International Monetary Fund.

Davies, J. B., Lluberas, R., & Shorrocks, A. F. (2017). Estimating the level and distribution of global wealth, 2000-2014. *Review of Income and Wealth*, *63*(4), 731–759.

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

Davies, J. B., & Shorrocks, A. F. (2000). The distribution of wealth. In *Handbook of income distribution* (pp. 605–675). Elsevier.

De Nardi, M. (2004). Wealth inequality and intergenerational links. *The Review of Economic Studies*, *71*(3), 743–768.

De Nardi, M., & Yang, F. (2014). Bequests and heterogeneity in retirement wealth. *European Economic Review*, *72*, 182–196.

de Haan, J., & Sturm, J.-E. (2017). Finance and income inequality: A review and new evidence. *European Journal of Political Economy*, *50*, 171–195.

Dell, F., Piketty, T., & Saez, E. (2007). Top incomes over the twentieth century: A contrast between continental european and english-speaking countries. In A. B. Atkinson & T. Piketty (Eds.). Oxford University Press.

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

Estevadeordal, A., & Taylor, A. M. (2013). Is the washington consensus dead? growth, openness, and the great liberalization, 1970s–2000s. *The Review of Economics and Statistics, 95*(5), 1669–1690.

Faust, J., Gilchrist, S., Wright, J. H., & Zakrajsek, E. (2013). Credit spreads as predictors of real-time economic activity: A bayesian model-averaging approach. *The Review of Economics and Statistics, 95*(5), 1501–1519.

Feldkircher, M., Horvath, R., & Rusnak, M. (2014). Exchange Market Pressures during the Financial Crisis: A Bayesian Model Averaging Evidence. *Journal of International Money and Finance, 40*, 21–41.

Feldkircher, M., & Zeugner, S. (2009). *Benchmark priors revisited: On adaptive shrinkage and the supermodel effect in bayesian model averaging* (Working Paper No. 09/202). International Monetary Fund.

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

George, E. I. (2010). Dilution priors: Compensating for model space redundancy. In *Borrowing strength: Theory powering applications–a festschrift for Lawrence D. Brown* (pp. 158–165). Institute of Mathematical Statistics.

Gwartney, J., Lawson, R. A., & Hall, J. C. (2017). *Economic freedom of the world: 2017 annual report* (tech. rep.). Fraser Institute.

Hasan, I., Horvath, R., & Mares, J. (2018). What type of finance matters for growth? bayesian model averaging evidence. *World Bank Economic Review, 32*(2), 410–427.

Havranek, T., Horvath, R., Irsova, Z., & Rusnak, M. (2015). Cross-country heterogeneity in intertemporal substitution. *Journal of International Economics, 96*(1), 100–118.

Hendricks, L. (2007). How important is discount rate heterogeneity for wealth inequality? *Journal of Economic Dynamics and Control, 31*(9), 3042–3068.

Islam, M. R. (2018). Wealth inequality, democracy and economic freedom. *Journal of Comparative Economics, 46*(4), 920–935.

Jakobsen, K., Jakobsen, K., Kleven, H., & Zucman, G. (2018). *Wealth taxation and wealth accumulation: Theory and evidence from denmark* (Working Paper No. 24371). National Bureau of Economic Research.

Karl, A., & Lenkoski, A. (2012). *Instrumental variable bayesian model averaging via conditional bayes factors* (tech. rep.). Heidelberg University.

Kass, R. E., & Raftery, A. E. (1995). Bayes factors. *Journal of the American Statistical Association*, *90*(430), 773–795.

Katic, P., & Leigh, A. (2016). Top wealth shares in australia 1915–2012. *Review of Income and Wealth*, *62*(2), 209–222.

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

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

Koop, G., Leon-Gonzalez, R., & Strachan, R. (2012). Bayesian model averaging in the instrumental variable regression model. *Journal of Econometrics*, *171*(2), 237–250.

Koop, G., Poirier, D. J., & Tobias, J. L. (2007). *Bayesian econometric methods* (G. Koop, Ed.). Cambridge University Press.

Kopczuk, W., & Saez, E. (2004). Top wealth shares in the united states, 1916–2000: Evidence from estate tax returns. *National Tax Journal*, *57*(2), 445–487.

Kopecky, K. A., & Koreshkova, T. (2014). The impact of medical and nursing home expenses on savings. *American Economic Journal: Macroeconomics*, *6*(3), 29–72.

Kuhn, M., Schularick, M., & Steins, U. I. (2017). *Income and wealth inequality in america, 1949–2016* (Discussion Paper No. 12218). Centre for Economic Policy Research.

Law, S. H., & Singh, N. (2014). Does too much finance harm economic growth? *Journal of Banking & Finance*, *41*, 36–44.

Lenkoski, A., Eicher, T. S., & Raftery, A. E. (2014). Two-stage bayesian model averaging in endogenous variable models. *Econometric reviews*, *33*(1-4), 122–151.

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

Lusardi, A., Michaud, P.-C., & Mitchell, O. S. (2017). Optimal financial knowledge and wealth inequality. *Journal of Political Economy*, *125*(2), 431–477.

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

Milanovic, B. (2016). *Global inequality*. 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.

Nardi, M. D., & Fella, G. (2017). Saving and wealth inequality. *Review of Economic Dynamics*, *26*, 280–300.

Pástor, L., & Veronesi, P. (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., & Zucman, G. (2014). Capital is back: Wealth-income ratios in rich countries 1700–2010. *The Quarterly Journal of Economics*, *129*(3), 1255–1310.

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

Roine, J., & Waldenström, D. (2009). Wealth concentration over the path of development: Sweden, 1873–2006. *The Scandinavian Journal of Economics*, *111*(1), 151–187.

Roine, J., & Waldenström, D. (2015). Long-run trends in the distribution of income and wealth. In *Handbook of income distribution* (pp. 469–592). Elsevier.

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

Scheidel, W. (2017). *The great leveler: Violence and the history of inequality from the stone age to the twenty-first century*. Princeton University Press.

Spolaore, E., & Wacziarg, R. (2009). The diffusion of development. *The Quarterly Journal of Economics*, *124*(2), 469–529.

Staiger, D., & Stock, J. H. (1997). Instrumental variables regression with weak instruments. *Econometrica*, *65*(3), 557–586.

Svirydzenka, K. (2016). *Introducing a new broad-based index of financial development* (Working Paper No. 16/5). International Monetary Fund.

Wright, J. H. (2008). Bayesian model averaging and exchange rate forecasts. *Journal of Econometrics*, *146*(2), 329–341.

Zeugner, S. (2011). *Bayesian model averaging with bms.*

Zucman, G. (2019). Global wealth inequality. *Annual Review of Economics,*
11(1), 109–138.

Appendix

3.A   Additional robustness checks

Table 3.7: 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 3.8: 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 3.9: Dependent variable - average Gini index (wealth) 2010-2016, 73 observations, relative redistribution measure

	PIP	Post Mean	Post SD
Value added in agriculture	1.00	-0.51152	0.15591
Financial institutions efficiency	0.99	-0.28741	0.11147
Access to financial institutions	0.98	-0.34837	0.15459
Redistribution (rel.)	0.95	-0.27535	0.14043
Outward orientation	0.94	0.23308	0.11250
Financial market depth	0.81	0.34002	0.21938
Education index (UN)	0.72	-0.22528	0.20282
Number of war years	0.59	0.08973	0.10332
Economic freedom index (adjusted)	0.36	-0.08389	0.15606
Labour market regulation	0.32	0.03829	0.07734
Natural resources rents	0.28	0.04065	0.08833
Financial institutions depth	0.28	0.10702	0.21832
Average GDP growth	0.28	-0.03598	0.07976
Rule of law	0.26	0.07442	0.17734
Leftwing orientation	0.22	-0.02359	0.06261
Net foreign direct investment	0.20	-0.02042	0.05956
Net national savings	0.20	0.02747	0.08091
Government expenditures	0.16	0.01994	0.06646
Bank capital regulations	0.11	-0.00826	0.03810
Population density	0.10	-0.00737	0.03893
Civ. liberties and Pol. rights	0.09	-0.00684	0.05487
Business conditions	0.09	-0.00679	0.03889
GDP level in 1990	0.09	-0.00754	0.08113
Public education expenditures	0.09	0.00452	0.03209
Financial openness (Chinn-Ito)	0.08	0.00371	0.04077
Banking diversification	0.08	-0.00453	0.02891
Financial liberalization (EFW)	0.08	-0.00225	0.04299
Active banking restrictions	0.08	-0.00396	0.03201
Latin America dummy	0.07	0.00613	0.08853
Technological progress	0.07	-0.00810	0.06770
Financial markets efficiency	0.06	-0.00027	0.03059
Inflation	0.06	0.00238	0.02706
Labour force participation	0.06	0.00036	0.02077
Life expectancy	0.06	0.00055	0.04579
Population growth	0.06	0.00076	0.03609
Value added in industry	0.05	-0.00063	0.02761
Revolutions and coups	0.05	0.00069	0.02121

Table 3.10: 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

3.B   List of countries

Table 3.11: List of countries

Argentina	India	Peru
Armenia	Ireland	Philippines
Australia	Israel	Poland
Austria	Italy	Portugal
Bangladesh	Jordan	Russia
Bolivia	Kenya	Singapore
Botswana	Korea, South	Slovakia
Brazil	Kyrgyzstan	Slovenia
Bulgaria	Latvia	South Africa
Canada	Lithuania	Spain
Colombia	Macedonia	Sri Lanka
Costa Rica	Malawi	Sweden
Croatia	Malaysia	Switzerland
Czech Republic	Mauritius	Tanzania
Ecuador	Mexico	Thailand
Egypt	Moldova	Tunisia
Estonia	Morocco	Turkey
Finland	Nepal	Uganda
France	Netherlands	Ukraine
Germany	New Zealand	United Kingdom
Ghana	Nigeria	United States
Greece	Norway	Uruguay
Hungary	Pakistan	Venezuela
Chile	Panama	
Iceland	Paraguay	

3.C Grouping of explanatory variables

Table 3.12: Explanatory Variables Sorted into Groups

GROUP	VARIABLES
Economic	Value added in agriculture Value added in industry Outward orientation Redistribution Net national savings Net foreign direct investment Average GDP growth GDP level in 1990 Inflation Government expenditures Public education expenditures Technological progress Labor force participation
Financial	Financial institutions efficiency Access to financial institutions Financial market development Financial institutions development Financial markets efficiency
Political	Number of war years Leftwing orientation Revolutions and coups Civ. liberties and pol. rights
Institutional	Education index (UN) Economic freedom index (adjusted) Rule of law
Regulatory	Labor market regulation Banking diversification Active banking restrictions Bank capital regulations Financial openness (Chinn-Ito) Business conditions Financial liberalization index (EFW)
Geographical / natural	Natural resource rents Population density Latin America dummy Population growth Life expectancy

3.D Descriptive statistics, correlation matrix

Table 3.13: Descriptive statistics

	Min.	Mean	Max.	Std.dev.
Access to financial institutions	0.02	0.36	0.96	0.26
Active banking restrictions	3.75	7.20	11.00	1.59
Average GDP growth	-0.02	0.02	0.06	0.01
Bank capital regulations	2.00	6.64	10.00	1.61
Banking diversification	0.00	1.32	2.00	0.46
Business conditions	-0.66	-0.28	1.53	0.36
Civ. liberties and Pol. rights	1.00	2.88	5.41	1.42
Economic freedom index (adjusted)	0.48	0.70	0.89	0.10
Education index (UN)	0.27	0.63	0.89	0.15
Financial institutions depth	0.02	0.31	0.86	0.24
Financial institutions efficiency	0.28	0.58	0.76	0.12
Financial liberalization (EFW)	4.01	7.34	9.49	1.52
Financial market depth	0.00	0.22	0.73	0.20
Financial markets efficiency	0.01	0.35	0.95	0.26
Financial openness (Chinn-Ito)	-1.47	0.41	2.39	1.26
GDP level in 1990	6.69	9.00	10.57	1.02
Government expenditures	4.75	16.14	27.48	4.63
Inflation	1.93	46.70	466.21	101.75
Labour force participation	0.00	0.00	0.00	0.00
Labour market regulation	0.46	1.67	2.78	0.51
Latin America dummy	0.00	0.18	1.00	0.39
Leftwing orientation	0.00	8.81	30.00	8.37
Life expectancy	45.51	68.88	78.04	7.86
Natural resources rents	0.00	3.49	31.66	5.30
Net foreign direct investment	0.09	2.95	12.56	2.42
Net national savings	-8.54	8.85	30.00	6.51
Number of war years	0.00	2.38	21.00	4.57
Outward orientation	-0.33	-0.03	0.19	0.08
Population density	2.22	164.99	4547.96	536.87
Population growth	-0.57	1.24	3.62	1.04
Public education expenditures	1.24	4.27	11.18	1.54
Redistribution	-3.40	9.41	22.37	7.07
Revolutions and coups	0.00	2.40	23.00	4.51
Rule of law	-1.23	0.39	1.96	0.95
Technological progress	-1.32	0.37	1.29	0.66
Value added in agriculture	0.41	12.26	45.27	11.79
Value added in industry	16.15	30.71	51.29	6.79

Table 3.14: Correlation matrix

	GiniWealth	NatRes	PopGrowth	GovExp	NNSavings	EducExp	Infl	VAI	VAA	NetFDI	RuleWB	GDP90	Ygrowth	LifeExp90	LFPart90	PopDens90	RevCoups	WarYears	EcoFreedom	FinLib	CLandPR	OutwardO	LatAm	ChinnIto	LeftWing	ActivRestrict	CapitalReg	DiversIndex	LAMRIG	Tech	EducIndex	FID	FIA	FIE	FMD	FME	BussCond
NatRes	0.35																																				
PopGrowth	0.24	0.44																																			
GovExp	-0.19	-0.32	-0.43																																		
NNSavings	0.34	0.14	0.42	-0.36																																	
EducExp	-0.03	-0.10	-0.19	0.58	-0.20																																
Infl	0.22	0.06	-0.06	-0.12	-0.14	-0.11																															
VAI	0.35	0.24	-0.18	0.00	0.32	0.03	0.20																														
VAA	-0.08	0.41	0.52	-0.49	-0.02	-0.29	0.04	-0.37																													
NetFDI	-0.21	-0.12	-0.29	0.29	-0.02	0.14	-0.02	0.13	-0.25																												
RuleWB	-0.13	-0.42	-0.41	0.48	-0.02	0.26	-0.36	-0.04	-0.64	0.25																											
GDP90	-0.04	-0.45	-0.66	0.56	-0.18	0.36	-0.16	0.20	-0.85	0.26	0.75																										
Ygrowth	-0.09	-0.09	0.02	-0.18	0.43	-0.27	-0.26	0.20	-0.08	0.08	0.30	-0.01																									
LifeExp90	-0.07	-0.54	-0.59	0.44	-0.07	0.33	-0.16	0.19	-0.83	0.24	0.67	0.90	0.04																								
LFPart90	-0.17	-0.15	-0.06	0.18	-0.11	0.14	-0.07	-0.05	-0.09	0.11	0.23	0.19	0.07	0.17																							
PopDens90	0.00	-0.13	0.12	-0.21	0.44	-0.19	-0.09	0.00	-0.09	0.44	0.14	0.08	0.27	0.08	0.00																						
RevCoups	0.25	0.32	0.33	-0.45	0.16	-0.15	0.51	0.12	0.19	-0.20	-0.46	-0.39	-0.14	-0.32	-0.13	-0.09																					
WarYears	0.32	0.17	0.30	-0.28	0.25	-0.32	-0.03	-0.06	0.28	-0.31	-0.26	-0.34	0.14	-0.31	-0.16	-0.02	0.02																				
EcoFreedom	-0.20	-0.46	-0.40	0.47	-0.13	0.24	-0.27	-0.05	-0.69	0.39	0.85	0.76	0.23	0.70	0.20	0.21	-0.40	-0.34																			
FinLib	-0.15	-0.35	-0.36	0.39	-0.18	0.31	-0.15	0.02	-0.59	0.34	0.65	0.68	0.04	0.64	0.13	0.10	-0.21	-0.38	0.81																		
CLandPR	0.10	0.43	0.55	-0.44	0.17	-0.33	0.14	-0.05	0.67	-0.06	-0.76	-0.76	-0.04	-0.68	-0.22	0.14	0.23	0.27	-0.67	-0.63																	
OutwardO	0.41	0.50	-0.02	-0.14	0.16	0.06	0.07	0.42	0.03	-0.16	-0.01	0.04	0.01	-0.10	-0.16	-0.22	0.19	0.08	-0.16	-0.14	-0.15																
LatAm	0.28	0.14	0.23	-0.38	0.05	-0.04	0.41	0.20	-0.07	-0.11	-0.34	-0.15	-0.22	0.01	-0.06	-0.12	0.53	-0.10	-0.16	0.05	0.05	0.11															
ChinnIto	-0.13	-0.29	-0.42	0.35	-0.01	0.26	-0.13	-0.03	-0.54	0.36	0.63	0.65	0.10	0.59	0.04	0.14	-0.24	-0.32	0.74	0.84	-0.59	-0.09	-0.09														
LeftWing	-0.13	-0.12	-0.18	0.18	-0.17	0.23	-0.06	-0.10	-0.15	-0.05	0.26	0.13	-0.08	0.15	-0.15	-0.13	-0.17	-0.06	0.08	-0.02	-0.24	0.06	0.03	-0.05													
ActivRestrict	0.00	0.22	0.49	-0.31	0.11	-0.09	-0.02	-0.10	0.42	-0.23	-0.43	-0.53	0.22	-0.45	0.00	-0.02	0.27	0.15	-0.40	-0.37	0.41	-0.11	0.24	-0.50	-0.09												
CapitalReg	0.02	-0.01	0.23	-0.08	0.14	-0.01	0.00	-0.15	0.23	-0.02	-0.19	-0.28	0.05	-0.30	-0.04	0.08	0.16	0.22	-0.26	-0.19	0.29	-0.09	-0.12	-0.25	-0.15	0.27											
DiversIndex	-0.04	-0.19	-0.20	0.23	-0.05	0.25	-0.10	0.12	-0.36	0.20	0.27	0.35	-0.06	0.32	-0.05	0.05	-0.24	-0.06	0.29	0.40	-0.25	-0.05	-0.02	0.41	0.01	-0.30	-0.04										
LAMRIG	-0.08	-0.10	-0.27	0.15	-0.15	0.05	0.20	0.06	-0.05	0.03	-0.20	0.00	-0.21	0.06	0.06	-0.18	0.12	-0.13	-0.17	-0.10	-0.01	-0.05	0.21	-0.07	0.09	-0.03	0.05	-0.12									
Tech	-0.07	-0.44	-0.67	0.60	-0.25	0.40	-0.10	0.17	-0.82	0.33	0.72	0.93	-0.08	0.88	0.16	0.04	-0.37	-0.40	0.73	0.67	-0.68	-0.02	-0.12	0.61	0.17	-0.49	-0.25	0.40	0.02								
EducIndex	-0.11	-0.37	-0.69	0.58	-0.28	0.40	-0.02	0.19	-0.75	0.34	0.70	0.87	-0.03	0.80	0.15	-0.01	-0.31	-0.29	0.72	0.72	-0.73	0.05	-0.14	0.68	0.12	-0.54	-0.32	0.33	-0.01	0.88							
FID	0.08	-0.26	-0.24	0.37	0.06	0.23	-0.24	0.01	-0.64	0.21	0.81	0.71	0.15	0.63	0.08	0.18	-0.32	-0.20	0.74	0.56	-0.61	0.12	-0.22	0.56	0.13	-0.46	-0.25	0.30	-0.29	0.67	0.61						
FIA	-0.20	-0.41	-0.52	0.44	-0.19	0.18	-0.16	-0.03	-0.71	0.16	0.71	0.79	0.09	0.72	0.23	-0.01	-0.30	-0.30	0.66	0.55	-0.73	-0.07	-0.18	0.54	0.13	-0.48	-0.20	0.24	0.06	0.74	0.69	0.73					
FIE	-0.18	-0.19	0.03	0.16	0.41	0.06	-0.48	-0.05	-0.29	0.10	0.52	0.20	0.37	0.27	0.05	0.19	-0.22	-0.13	0.38	0.17	-0.26	-0.02	-0.29	0.23	0.17	-0.19	-0.11	0.13	-0.09	0.16	0.09	0.48	0.29				
FMD	0.19	-0.19	-0.16	0.23	0.19	0.13	-0.27	0.03	-0.55	0.16	0.73	0.64	0.15	0.56	0.03	0.25	-0.26	-0.03	0.63	0.48	-0.50	0.16	-0.28	0.53	0.05	-0.49	-0.14	0.28	-0.30	0.59	0.53	0.91	0.62	0.45			
FME	0.02	-0.35	-0.36	0.27	-0.01	0.13	-0.23	-0.02	-0.39	0.10	0.46	0.52	0.07	0.45	-0.10	0.12	-0.24	-0.01	0.39	0.30	-0.38	0.14	-0.35	0.30	0.14	-0.38	0.07	0.26	0.04	0.50	0.44	0.51	0.47	0.12	0.58		
BussCond	0.16	0.39	0.47	-0.31	0.16	-0.11	0.26	0.18	0.33	-0.25	-0.51	-0.52	-0.22	-0.50	-0.13	-0.16	0.48	0.07	-0.56	-0.36	0.30	0.18	0.45	-0.38	0.03	0.29	0.14	-0.17	0.22	-0.50	-0.47	-0.42	-0.37	-0.19	-0.41	-0.42	
Redist	-0.33	-0.35	-0.64	0.67	-0.42	0.35	-0.28	-0.11	-0.49	0.31	0.63	0.63	-0.06	0.51	0.11	-0.08	-0.46	-0.30	0.61	0.51	-0.61	-0.02	-0.42	0.51	0.22	-0.40	-0.23	0.27	0.12	0.63	0.64	0.50	0.59	0.24	0.38	0.49	-0.47

3.E Top models by their posterior model probability, group PIPs

Table 3.15: Top 3 models according to their posterior mode probabilities

Variable	Model 1	Model 2	Model 3
Access to financial institutions	1	1	1
Value added in agriculture	1	1	1
Financial institutions efficiency	1	1	1
Outward orientation	1	1	1
Financial market depth	1	1	1
Education index (UN)	1	1	1
War years	1	1	1
Redistribution	1	0	1
Average GDP growth	0	0	1

Note: 1 marks inclusion of the variable in the model, whereas 0 suggests otherwise. The variables not listed were not included in neither of the models.

Table 3.16: Group posterior inclusion probabilities

Group	PIP
Financial	1.00
Economic	1.00
Political	0.85
Institutional	0.70
Geographical	0.65
Regulatory	0.34

3.F OLS estimates of the restricted models

Table 3.17: Output of the linear regression specifications, dependent variable GiniWealth

	(1)	(2)
Access to financial institutions	−0.376***	−0.411***
	(0.140)	(0.140)
Value added in agriculture	−0.637***	−0.626***
	(0.141)	(0.143)
Financial institutions efficiency	−0.356***	−0.377***
	(0.100)	(0.100)
Outward orientation	0.319***	0.320***
	(0.086)	(0.087)
Financial markets depth	0.470***	0.522***
	(0.124)	(0.121)
Education index	−0.388**	−0.413**
	(0.157)	(0.158)
Number of war years	0.146	
	(0.091)	
Redistribution	−0.213*	−0.230*
	(0.114)	(0.115)
Observations	73	73
R^2	0.574	0.556
Adjusted R^2	0.520	0.509
Residual Std. Error	0.693 (df = 64)	0.701 (df = 65)
F Statistic	10.761*** (df = 8; 64)	11.645*** (df = 7; 65)

Note: $^*p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$. The specification of the model (1) corresponds to the model with the highest posterior model probability, whereas the model (2) containts the regressors with PIP > 0.5 in the baseline BMA estimation.

3.G Dataset description

Table 3.18: 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)
GDP90	Level of GDP per capita in 1990	PWT (9.0)
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
VAA	Agriculture, forestry, and fishing value added (% GDP). 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)
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	Campos & Nugent (2012)

Tech	Index on the level of technological development based 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 3.4: Top 10% wealth and income shares in OECD countries
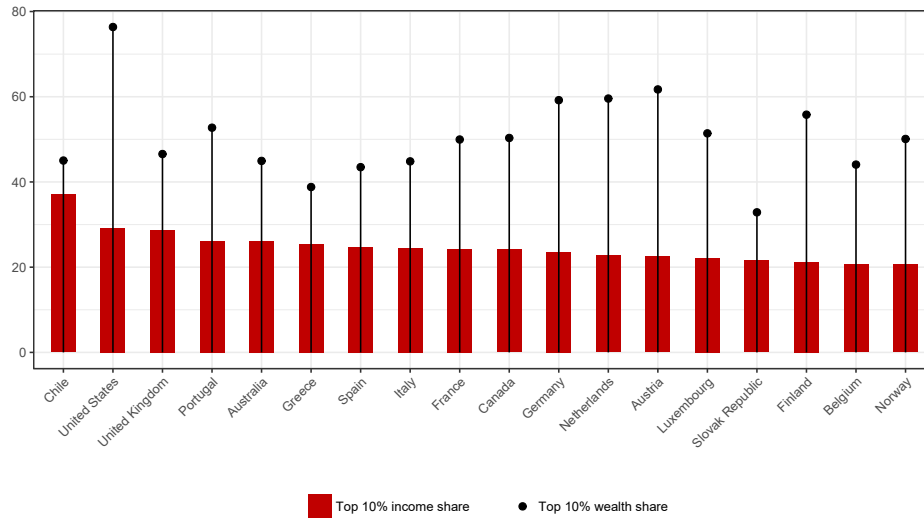
3.H Bayesian Model Averaging

First, consider the following linear model:

$$y = \alpha + X\beta + \varepsilon \qquad \varepsilon \sim N(0, \sigma^2 I) \tag{3.8}$$

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 Independent Identically Distributed (IID) error terms with variance σ^2.

BMA takes into consideration all possible combinations of X from equation 3.8 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:

$$y = \alpha_i + X_i\beta_i + \varepsilon \qquad \varepsilon \sim N(0, \sigma^2 I) \tag{3.9}$$

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

$$p(\beta|y, X) = \frac{p(y, X|\beta)p(\beta)}{p(y, X)} \tag{3.10}$$

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 $M_1, ..., M_i$. In the case of K regressors, there are $M_1, ..., M_i$ 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:

$$p(\beta_i|M_i, y, X) = \frac{p(y|\beta_i, M_i, X)p(\beta_i|M_i)}{p(y|M_i, X)} \tag{3.11}$$

Next, we describe the averaging principle of BMA and individual components of equation 3.10.

Posterior Model Probability

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

$$p(M_i|y, X) = \frac{p(y|M_i, X)p(M_i)}{p(y|X)} \tag{3.12}$$

where $p(y|M_i, X)$ is the 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.

$$p(M_i|y, X) \propto p(y|M_i, X)p(M_i) \tag{3.13}$$

We discuss the calculation of ML in detail in Subsection 3.H. 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:

$$p(\beta|y, X) = \sum_{i=1}^{2^K} p(\beta_i|M_i, y, X)p(M_i|y, X) \tag{3.14}$$

where $p(M_i|y, X)$ is the PMP of the corresponding model M_i from equation 3.12. The point estimates are obtained by taking expectations:

$$E(\beta|y, X) = \sum_{i=1}^{2^K} E(\beta_i|M_i, y, X)p(M_i|y, X) \tag{3.15}$$

$E(\beta|y, X)$ 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:

$$E(\beta_i|y, X, g, M_i) = \frac{g}{1+g}\hat{\beta}_i \tag{3.16}$$

with $\hat{\beta}_i$ 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:

$$
\begin{aligned}
Var(\beta|y, X) = &\sum_{i=1}^{2^K} p(M_i|y, X)Var(\beta_i|M_i, y, X) \\
&+ \sum_{i=1}^{2^K} p(M_i|y, X)(E(\beta_i|M_i, y, X) - E(\beta|y, X))^2
\end{aligned}
\tag{3.17}
$$

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 $E(\beta_i|M_i, y, X) - E(\beta|y, X))^2$. $E(\beta|y, X)$ represents the posterior mean from equation 3.15. 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:

$$Cov(\beta_i|y, X, g, M_i) = \frac{(y - \bar{y})'(y - \bar{y})}{N - 3} \frac{g}{1 + g} \left(1 - \frac{g}{1 + g}R_i^2\right)(X_i'X_i)^{-1} \quad (3.18)$$

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

Marginal Likelihood

ML can be calculated using equation 3.11 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

$$p(y|M_i, X) = \int_\beta p(y|\beta_i, M_i, X)p(\beta_i|M_i, X)\, d\beta_i \quad (3.19)$$

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):

$$p(y|M_i, X, g) = \int_0^\infty \int_\beta p(y|\beta_i, \sigma^2, M_i)p(\beta_i, \sigma^2|g)\, d\beta d\sigma \quad (3.20)$$

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

$$p(y|M_i, X, g) \propto (y - \bar{y})'(y - \bar{y})^{-\frac{N-1}{2}}(1 + g)^{-\frac{k_i}{2}}\left(1 - \frac{g}{1 + g}R_i^2\right)^{-\frac{N-1}{2}} \quad (3.21)$$

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 3.18, 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:

$$PIP = p(\beta_k \neq 0|y, X) = \sum_{i=1}^{2^K} p(M_i|\beta_k \neq 0, y, X) \qquad (3.22)$$

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:

$$p_{i,j} = min\left(1, \frac{p(M_j|y, X)}{p(M_i|y, X)}\right) \qquad (3.23)$$

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.

Chapter 4

Finance and Inequality - panel BMA approach

Abstract

We investigate the impact of financial development on income inequality differentiating between depth, efficiency and access to financial markets and institutions. We apply panel Bayesian model averaging framework to address model uncertainty to reveal that financial development has complex relationship with the income distribution within countries. The access to and efficiency of banking decrease income inequality. The size of the markets has no relevance for overall income inequality, but relates to the higher top income shares. Moreover, unemployment along with investment into nontangible assets increase income inequality while more redistribution imply lower levels of inequality.

4.1 Introduction

Financial development alters how much the economic opportunities depend on the individual skills, family endowments, social status or political connections as individual may depend on financial system to provide loans to start new business, attain education, or temporarily fund their consumption. The research in the area of financial development and income inequality is well established. Demirgüç-Kunt and Levine (2009), Claessens and Perotti (2007), and more recently de Haan and Sturm (2017) provide broad reviews of the topic. A similar theme emerges noting that the implications from theoretical contributions provide conflicting predictions about the relationship. The empirical results then bring evidence for both positive and negative effect. Although majority of the papers point towards finance tightening the distribution of income this result is not universal with some papers suggesting the opposite while other stress potential non-linearities.

A key divide appears between the effect of financial development on extensive and intensive margin. The extensive margin captures the extend to which individuals, who had not been using financial services before, gain access. On the other hand, the intensive margin describes growing use of finance by the agents who had already been using it before (Demirgüç-Kunt & Levine, 2009). Financial development on the extensive margin might lead to more equal opportunities and outcomes. Access to credit by previously disadvantaged groups allows human capital accumulation (Braun et al., 2019; Galor & Moav, 2004; Galor & Zeira, 1993) as well as formation and growth of new firms (Banerjee & Newman, 1993; Evans & Jovanovic, 1989), with more evenly distributed economic opportunities as a result[1].

On the contrary, intensive margin of financial development might disproportionately benefit the rich who may leverage financial services for their further benefit or to protect their existing rents. Greenwood and Jovanovic (1990) present a model where the finance is the key driver of inequality and the welfare gains accrued by the incumbents - primarily the rich - in the initial development stage. With time, more agents meet the fixed costs of joining the financial intermediaries and they enjoy higher returns. Consequently, the efficiency of resource allocation also increases, which enhances growth and reduces inequal-

---

[1]Having similar economic opportunities might decrease the cross-generational inequality, by diminishing the effect of e.g. parental wealth. Depending on the innate abilities and talents of the individuals, however, it may increase the inequality of income within every generation at the same time.

ity. Perotti and Volpin (2007) present a framework based on political economy. Their argument depends on a lobby for lower investor protection to prevent entrance of the new competitors. The politicians require higher bribe from the lobbyist the greater is their accountability for policy decisions. Thus, with increasing accountability, investor protection strengthens and spurs market entry and competition. The authors examine their prediction in a cross-section and show that better investor protection correlates with larger entry rates and higher firm density in more financially intensive sectors[2].

Financial development may also have indirect effect on income inequality through economic growth. Townsend and Ueda (2006) model how finance interacts with production and allocation of credit. If increased use of finance increases the demand for low- relatively to the high-skilled workers, then it may have equalizing consequences for income distribution. Empirical evidence by Beck et al. (2010) show that bank deregulation and increased competition in loan provision in the US primarily benefited the workers with income below the median. Similarly, Delis et al. (2014) provide evidence of bank deregulation and liberalization tightening the income distribution, although this effect is only present in countries with high-quality institutions. They attribute the effect to the changes in labour market conditions and relatively higher wages and working hours of the low-skilled workers following the reforms.

A set of distinct papers explores the relationship between inequality and growth while stressing financial markets imperfections in driving the outcomes. Income inequality and growth may intersect through varying channels. Accumulation of savings, unobservable effort, and investment project size favor the prediction of growth inducing inequality. Negative impact of inequality on human capital accumulation and entrepreneurial activity provide argument for the opposing view. Van der Weide and Milanovic (2018) report how income inequality in the US has different implications for the future income growth of the rich and the poor. High inequality seems to hurt the prospects of the poor while the top of the distribution is unaffected. The rich thus disproportionately benefit from higher inequality as their subsequent income exhibits faster growth. The authors attribute this effect to the political channel the rich use to lobby in favor of the policies which support their economic interests. Preferences of the rich are ultimately more likely to determine public policy than the

---

[2]In addition, they show that the most important factor of accountability is not the formal measure of democratic institutions, but newspaper readership which they interpret as broad awareness of policy choices and their outcomes.

preferences of the majority (Gilens & Page, 2014). High inequality together with a credit constraint and rich driving the political process result in low government spending and lasting inequality.

The literature does not converge on the conclusions even in the empirical cross-country and panel data studies. The papers link higher levels of financial development with lower levels of inequality (Beck et al., 2007; Gimet & Lagoarde-Segot, 2011; Hamori & Hashiguchi, 2012; Kunieda et al., 2014)[3]. On the other hand, several other estimate an inequality inducing effect of finance (de Haan & Sturm, 2017; Jauch & Watzka, 2016; Jaumotte et al., 2013). Finally, some authors claim there the relationship might be non-linear, conditional on a threshold value of financial development (Kim & Lin, 2011; Tan & Law, 2012) or institutional quality (Delis et al., 2014; Law & Singh, 2014).

Three papers are the closest to ours, each in a different respect. First, de Haan and Sturm (2017) examine different dimensions of finance on income inequality. Their results suggest that financial development, financial liberalization, and banking crises all increase pre-tax income inequality within countries. Additionally, they show that the effect of financial liberalization is conditional on democratic accountability. Higher accountability mitigates the impact of liberalization on inequality. On the contrary, the financial development, proxied by the credit to GDP ratio, has inequality increasing effect irrespective of the institutional background. Second, Naceur and Zhang (2016) take similar approach in considering multiple dimensions — the access, efficiency, and stability — of the financial sector when studying determinants of inequality and poverty, but they do not attempt to consider the indicators simultaneously. Third, Furceri and Ostry (2019) apply Weighted-average Least Squares (WALS) to identify robust determinants of income inequality. Their approach mirrors ours in accounting for model uncertainty in the estimation, but their focus is more general rather than focused primarily on finance. We provide synthesis and a natural extension to these papers by offering more detail on how finance in shapes income inequality. We examine multiple measures of inequality while specifically identifying the determinants of top income shares along with the determinants of the overall income distribution[4].

---

[3]For an extended list, we refer to de Haan and Sturm (2017).

[4]Captured by income Gini index.

4.2 Data and methodology

The key variable in the paper is the measure of income inequality. We want to examine how financial development affects income inequality and whether the effect might by different at the top quantiles of income distribution. As the overall measure of income inequality, we rely the after-tax Gini coefficient from Standardized World Income Inequality Database (SWIID) by Solt (2019), which is a standard resource in the literature[5]. Its critical advantage lies in the widespread coverage across countries and time and a unified methodology which provides a reasonable level of comparability. It typically takes values in the interval between 0 and 100 where the former suggests perfect equality (everyone in the economy enjoys the same income) and the latter perfect inequality (all the income goes to only a single unit). We depart from existing papers slightly in considering the after-tax rather than the before-tax income distribution as the dependent variable.

To explore the relationship in the top part of the distribution, we choose top income shares from the WID[6]. The surveys suffer from well-known issues of underrepresentation of the top income earners and the distortions resulting from self-reported character of the data. This can influence not only the top income shares originating from the survey data, but it may also distort the overall measures of inequality. The data in WID make use of income tax records in individual countries and the derived shares obtained using consistent methodology of Distributional National Accounts (DINA) are arguably more reliable relative to the survey-based measures which are the primary source of majority estimates of income distributions.

The data spans from 2000 to 2014. We follow the literature (Dabla-Norris et al., 2015; de Haan & Sturm, 2017) and average both the inequality measure (dependent variable) and the potential determinants (independent variables) across 3-year intervals. There are important reasons for looking at the averages than observation in individual years. Annual macroeconomic data are subject to fluctuations and the data on income inequality is noisy (Delis et al., 2014). Averaging should diminish the level of noise. On the top of that, the variables at the center of our analysis, e.g. stock market capitalization or credit to GDP, are likely to be affected by the business cycles and volatile on the yearly basis.

---

[5]There are alternative sources of for Gini coefficient, e.g. World Income Inequality Database (WIID) or Luxembourg Income Study (LIS), but each of them brings limitations in terms of comparability or coverage.

[6]The methodology and guidelines to database are provided by Alvaredo et al. (2016).

Similar argument holds for top income shares, as they depend, among other things, on the bonuses paid out each year as well as capital income. We want to explore the long-term rather than the short-term relationship and that guides the choice of averaged data. Faced against the trade-off between length of the averaging periods and available observations in the time dimension, we take a compromise of three years in contrast to the literature, where the 5-year intervals generally apply. The availability of financial development indicators limits the analysis to a period from 2000 onward and we prefer to keep at least 5 unique time periods to just three under the case of 5-year average[7].

Table 4.1 reports the summary statistics of the income inequality variables and financial development indicators.

Table 4.1: Summary statistics of selected variables

Variable	Mean	St. Dev.	Min	Max
After-tax Gini index	36.38	8.12	22.88	61.16
Top 10% income share	0.42	0.12	0.24	0.71
Top 1% income share	0.14	0.06	0.05	0.38
FIA	0.42	0.32	0.01	1.00
FIE	0.60	0.13	0.11	0.81
FID	0.37	0.30	0.01	1.00
FMD	0.33	0.32	0.00	0.99

Table 4.2: Correlation matrix of selected variables

After-tax Gini index	.						
Top 10% income share	0.47	.					
Top 1% income share	0.39	0.84	.				
FIA	-0.14	-0.09	-0.12	.			
FIE	-0.14	-0.10	-0.06	0.28	.		
FID	-0.07	0.12	0.06	0.60	0.24	.	
FMD	0.03	0.2	0.13	0.36	0.1	0.40	.

We obtain the financial development indicators from GFDD. The database offers detailed indicators along four dimensions of financial systems and allows to estimate the affect of changes in access, size, efficiency, and stability of financial markets. Furthermore, we can distinguish between banking sector and financial markets in all these dimensions. The data for access and stability of stock markets remains sparse in the concerned period we must leave them out

---

[7]Nevertheless, we run the estimation with 5-year averages of data as a robustness check and find no critical qualitative differences compared to the baseline.

of analysis. We use the version of financial indicators from Svirydzenka (2016). The authors make use of principal component analysis in order to construct aggregate indicators in each characteristic of financial sector. In summary, we have indicators of financial institutions depth (FID), financial markets depth (FMD), access to financial institutions (FIA), efficiency of financial markets (FME), and institutions (FIE)[8]. We report the composition of each indicator in Table 4.6.

Figure 4.1: Gini Coefficient and top shares
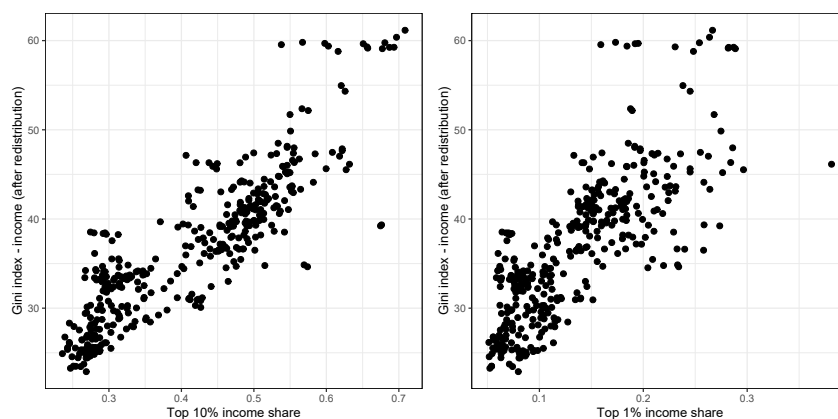
We build the choice of other explanatory variables on a reviews of income inequality drivers (Nolan et al., 2019; Roine et al., 2009), related study of finance-inequality nexus (de Haan & Sturm, 2017), and a more general inquiry into the robust determinants of income inequality (Furceri & Ostry, 2019). The potential regressors could be categorized in several groups. They control for economic and financial development, demographics, globalization, and institutional background. Table 4.7 reports all the control variables and their sources.

Methodologically, we rely on the BMA approach which conveniently addresses the issue of model uncertainty with a large number of potential regressors. The advantages and statistical properties of the BMA have been described in Koop (2003). In application to the panel data, we make use of Frisch-Waugh-Lovell theorem and demean all the variables using time averages for individual observations. Using the time-demeaned observations in the estimation is equivalent to the estimate using the dummy variables for individual cross-sectional units. The key assumptions in BMA are on parameter and model priors. For the parameter prior, we turn to so-called hyper-g prior. The prior provides more

---

[8]Svirydzenka (2016) extrapolate the indicators from top to bottom if the original variables are unavailable, we make sure that that at least one variable is available for the construction of the index and no artificial correlation introduced to the data.

robust results than some other traditionally applied g priors such as UIP, BRIC (Feldkircher & Zeugner, 2012). As for the model priors, the baseline estimate relies on the uniform model prior. We choose the model prior to remain agnostic about the prior probability of each examined model. While uniform prior assigns the same prior probability to each model, the distribution of the prior model space is concentrated around $k/2$, where k is the number of potential covariates, and it may consequentially gravitate towards larger model sizes and higher number of covariates[9].

4.3 Results

We examine the determinants of inequality in the panel BMA framework and present the results in the following sections. We start with a model where we capture the overall inequality by Gini index in subsection 4.3.1. We then continue to estimations where we consider the shares of income going to the top 10% and top 1% of the income distribution as our dependent variable. We check the robustness of our estimates by employing alternative model and parameter priors throughout the analysis.

### 4.3.1 Gini index of income distribution

We focus the analysis on the relationship between the indicators representing various aspects of financial development and income inequality. Figure 4.2 outlines the expected link after we have demeaned the variables using the cross-sectional averages. The relationship is not particularly strong, but we observe negative correlation between Gini index and indicators of access and efficiency of financial institutions, as suggested by a linear estimate. For size indicators of financial market and institutions, the link appears much weaker.

Table 4.3 reports the baseline results. Overall, we have 16 variables with PIP above 0.8. The number of unique relevant regressors effectively shrinks by two if we abstract from the quadratic terms of the GDP per capita and the education index. Most of the estimated posterior means exhibit expected signs.

The only financial indicators which occur among the top regressors are access and efficiency of financial institutions with PIPs of 1 and 0.88, respectively. The posterior mean on the coefficients in both dimension is negative so higher

---

[9]See Ley and Steel (2009) for details.

Figure 4.2: Gini Coefficient and Financial Development Indicators
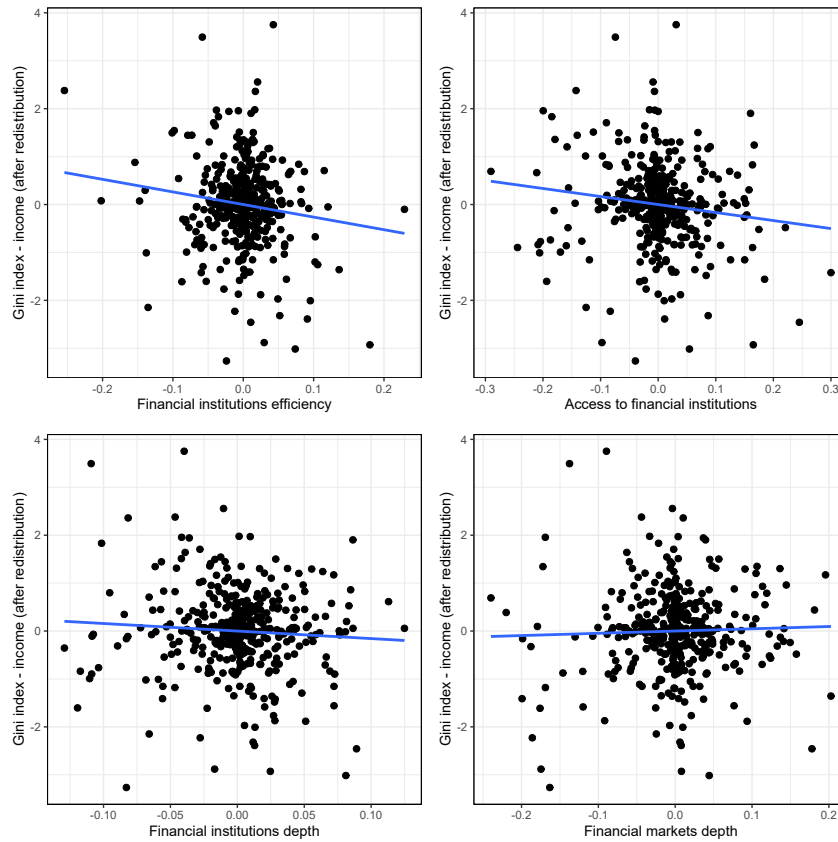
levels of access and efficiency are associated with lower levels of income inequality. The inequality decreasing effect of access to finance on inequality mirrors Hasan et al. (2020) for wealth inequality, and partially also Furceri and Ostry (2019), Naceur and Zhang (2016) who document similar effect. The observation on inequality decreasing effect of access to finance supports also Claessens and Perotti (2007) who suggest that access may equalize economic opportunities and lead to a more evenly distributed income as well as with theoretical predictions (Banerjee & Newman, 1993; Braun et al., 2019; Galor & Moav, 2004). The efficiency of financial intermediation putting downward pressure on income inequality also has a precedent in Gimet and Lagoarde-Segot (2011)[10]. We fail to confirm that the efficiency of financial institutions is a robust determinant of inequality, however, as the PIP markedly decreases under alternative model priors. None of the size indicators of financial institutions or markets

---

[10]The authors measure efficiency of banking sector by the difference between lending rate and the deposit rate (spread). They argue higher spread reflects low competition and high transaction costs. The imperfections in the credit market can skew the credit to high-income, rich households who can provide significant collateral, reinforcing the existing inequality.

has high probability of inclusion.

Education expenditures (% share of GDP) along with the education index calculated using mean and expected years of schooling show inequality decreasing effect. This is in line with prediction of Deaton (2013), Goldin and Katz (2009) who claim that the skill-biased technological change should be mitigated by education. OECD (2011) finds similar evidence for a panel of advanced countries while Furceri and Ostry (2019) also suggest a negative relationship, although it is not fully robust to variable and sample selection. The effect of education diminishes at the higher levels of schooling as the quadratic term has also high PIP and positive posterior mean.

We find evidence for the Kuznets' hypothesis about the inequality and economic development. We include three regressors which primarily capture the level of development - GDP per capita along with its square term, share of value added in agriculture, and share of value added in industry. Exploring the results of the baseline, We find evidence for an inverted-U curve for GDP per capita and baseline PIPs for linear and square component. This suggests that the inequality tends to be lower at the initial stages of economic development, then increases as the economic output grows, and only starts decreasing after reaching a threshold. The PIP of 0.97 for value added in agriculture along with a negative posterior mean for its coefficient supports this idea further. The economies at lower stages of development generally report higher shares of agricultural sector which is also more labour intensive, i.e. not exacerbating the inequalities that stem from unequal distribution of capital. The level of unemployment is associated with elevated income inequality. The mechanism is direct through the lower share of income going to labour in case of high unemployment rates. The effect of unemployment is also documented on cross-section by Furceri and Ostry (2019). We also explore the effect of non-equipment investment[11], which we believe could proxy for the technological progress and skill-biased technological change. The PIP suggests positive correlation with income inequality as Dabla-Norris et al. (2015), Goldin and Katz (2009).

We rely on redistribution to capture the effect of taxes and social expenditure on income inequality. Our measure is the the difference between before-tax and after-tax Gini coefficient from the SWIID database. Therefore, we concen-

---

[11]We construct the indicator using the detail on capital investment prom PWT and split the overall investment into non-equipment (structures, transportation, and other assets - software / intellectual property products) and equipment investment (machinery, computers + communication equipment).

Table 4.3: BMA, baseline results. Dependent variable after-tax Gini
index, 394 observations.

	PIP	Post Mean	Post SD
Education expenditures	1.00	-0.14506	0.05042
GDP per capita	1.00	1.62811	0.56870
Unemployment	1.00	0.23629	0.05907
Non-equipment investment	1.00	0.14977	0.05285
Access to financial institutions	1.00	-0.24629	0.06342
Education index (UN)	1.00	-0.58853	0.23865
Redistribution	1.00	-0.22055	0.05051
Education index sq.	1.00	0.82252	0.22008
GDP per capita sq.	1.00	-1.44906	0.57565
Life expectancy	0.99	-0.22879	0.09750
Economic freedom	0.99	0.18518	0.06941
Value added in agriculture	0.97	-0.12361	0.05947
Government expenditures	0.95	0.12259	0.05743
Total population	0.95	-0.15378	0.08478
Financial institutions efficiency	0.88	-0.08374	0.05599
Inflation	0.86	0.16879	0.12487
Inflation sq.	0.66	-0.11127	0.11201
Value added in industry	0.62	-0.05825	0.06407
Equipment investment	0.44	-0.03383	0.05359
Financial markets depth	0.27	0.01554	0.03673
Gross domestic savings	0.27	-0.02022	0.04597
Social globalization	0.23	0.02365	0.06279
Restrictions on globalization	0.15	0.00874	0.03214
Trade openness	0.13	0.00615	0.02589
Left-wing orientation	0.11	0.00339	0.01720
Rule of law	0.10	-0.00333	0.01812
Net FDI (% GDP)	0.10	-0.00283	0.01575
Natural resources rents	0.08	-0.00223	0.01583
Chinn-Ito index	0.07	-0.00205	0.01780
Financial globalization	0.06	-0.00134	0.01466
Civil liberties & political rights	0.06	0.00075	0.01131
Financial institutions depth	0.05	0.00060	0.01316
GDP growth	0.05	0.00016	0.01255
Population growth	0.05	0.00055	0.01052
Political globalization	0.05	0.00000	0.01432

trate on the direct effects of policies on the household income. Given the global
nature of our data and its limitations, we cannot estimate the potential indirect
effects on the pre-tax distribution of income using, for example, top marginal
tax rates (Alvaredo et al., 2013) nor corporate tax rates (Fuest et al., 2018).
Nevertheless, the PIP of our indicator is very high and it negatively relates to
income inequality as expected. The government expenditures, an often used
regressor in the literature also has a perfect inclusion probability, but with
positive posterior mean. The intuitive first-order effect of government expendi-

ture should be through reduction of inequality through general social spending on transfers, education, and health. We account for these explicitly, however, with redistribution and education expenditures of the government. Anderson et al. (2017) introduce a meta-analysis where they show how the examined relationship depends on the type of spending considered and the measure of income inequality. Additionally, they suggest that the redistributive impact has not extended over the entire distribution, but has mostly centered towards middle-income groups. In line with their conclusions, our results suggest the effect of government spending might run in the positive direction when the key equalizing function have been accounted for or perhaps point towards reverse causality.

Life expectancy should proxy for changing demographics. We find a negative link between life expectancy and income inequality. Goldstein and Lee (2014) examine the channels between population ageing and inequality and argue that stretching the economic life-cycle is associated with larger within-group variance as a cohort ages. They claim this should pronounce inequality in older populations. On the other hand, if we consider retirement age, pension structure in many countries equalize income flows and therefore the older populations may report lower levels of inequality. The posterior mean of our estimated coefficient indicates the latter scenario.

Inflation is the only variable which could proxy for monetary policy and its influence on income inequality. It is among the relevant regressors with PIP of 0.86 and shows inequality inducing association. The interest in the effects of monetary policy, and macroprudential tools in particular, on inequality is relatively recent, following the introduction of unconventional measures following the Great Recession (Frost & van Stralen, 2018). Theoretically, the effect is ambiguous as high inflation of asset prices might benefit high-income households more as they receive higher shares of financial income. Also, the assets held by low-income households tend to be much more liquid, thus inflation hurts them more relatively to the high-income ones. On the contrary, cut in rates usually benefits the borrowers and increased economic activity benefits the bottom-part of income distribution (Furceri & Ostry, 2019). Our evidence supports the view of inflation enhancing income inequality, at least up to a threshold, as its square term is borderline on the inclusion, but negative in terms of posterior mean of its coefficient. This would suggest that the above-mentioned theoretical effects interact and manifest with different strength at varying inflation levels.

The index of the economic freedom of the world describes the overall business conditions by considering regulatory and legal environment. More economic freedom to trade and run daily business makes it easier to exploit economic opportunities and the high PIP with positive posterior mean of the coefficient point to economic freedom making the distribution of income less equal. We consider many other potential explanatory variables, but in the case of Gini index, they show low PIPs. We do not find any measure of globalization, institutions, or trade openness relevant for the overall distribution of income. In the next section, we concentrate on the top income shares and whether the top part of the distribution where we observe partially distinct results.

4.3.2   Top income shares

Financial development may influence various part of the income distribution differently. We therefore follow with baseline estimates with the top income shares as dependent variables. Table 4.4 reports the results for top 10% share and Table 4.5 for the top 1% share. There is large overlap of the most important determinants for the top 10% income share and Gini coefficient. GDP per capita, life expectancy, government expenditures, education index (but not expenditures), and inflation remain among the relevant regressors and their posterior means are consistent with the estimation for the overall income distribution. However, PIPs of some of the variables decline significantly and some other become relevant. Figure 4.3 provides a visual comparison of the inclusion probabilities.

In the case of the Top 10% share, education expenditures, non-equipment investment, unemployment, redistribution, and an index of economic freedom drop out. With the exception of the economic freedom, there are good reasons to believe these factors mainly drive lower and middle-part of the income distribution, rather than the very top. While education expenditures may support public education system and allow for human capital accumulation in the low-income households, such effect might not be as relevant for the concentration at the top. We have discussed previously how redistribution policies mostly affect the middle quantiles of the distribution and high unemployment rates traditionally do not concern the well educated high-income households and individuals. Also share of value added in agriculture now has a low PIP. The inclusion of non-equipment investment also decreases, while it retains the positive posterior mean. Most importantly, depth of financial markets and fi-

Table 4.4: BMA, baseline results. Dependent variable Top 10% share, 394 observations.

	PIP	Post Mean	Post SD
Natural resources rents	1.00	-0.15595	0.04773
GDP per capita	1.00	2.13915	0.54791
Life expectancy	1.00	-0.53327	0.09806
Financial institutions depth	1.00	0.20288	0.05638
Access to financial institutions	1.00	-0.25218	0.06712
Financial markets depth	1.00	0.19376	0.04976
GDP per capita sq.	1.00	-1.80042	0.55408
Government expenditures	1.00	0.15638	0.05565
Rule of law	1.00	-0.12607	0.04665
Education index (UN)	1.00	-0.49573	0.22152
Education index sq.	1.00	0.58180	0.20423
Equipment investment	1.00	-0.13953	0.05578
Trade openness	0.98	0.12632	0.05604
Inflation	0.80	0.06758	0.05407
Gross domestic savings	0.65	0.06566	0.06764
Left-wing orientation	0.63	0.04567	0.04858
Total population	0.57	0.07224	0.08621
Financial institutions efficiency	0.55	-0.04309	0.05278
Non-equipment investment	0.49	0.03864	0.05320
Value added in industry	0.31	-0.02652	0.05253
Financial globalization	0.22	-0.01390	0.03673
Value added in agriculture	0.18	-0.01163	0.03405
Unemployment	0.18	-0.01019	0.03113
Restrictions on globalization	0.13	0.00637	0.02398
Civil liberties & political rights	0.12	0.00529	0.02137
GDP growth	0.12	0.00608	0.02464
Net FDI (% GDP)	0.07	-0.00217	0.01377
Redistribution	0.07	-0.00243	0.01571
Chinn-Ito index	0.06	0.00170	0.01373
Population growth	0.05	0.00097	0.01043
Economic freedom	0.04	0.00055	0.01416
Education expenditures	0.04	-0.00062	0.01030
Social globalization	0.04	-0.00004	0.01918
Political globalization	0.04	0.00060	0.01279
Inflation sq.	0.03	-0.00045	0.01581

nancial institutions now exhibit perfect PIPs and they seem to be associated with income distributions more concentrated at the top. The access to financial institutions remains relevant and negatively correlated with inequality. Among other variables with higher PIPs, we have natural resources rents, rule of law, equipment investment, and trade openness. For the natural resources rents, we get a negative posterior mean. The evidence is in line with Goderis and Malone (2011), who describe a mechanism of income equalizing natural resource booms through the benefits for unskilled workers in labour intensive sector. A positive

link between inequality and trade openness has been suggested by Dabla-Norris et al. (2015), Jaumotte et al. (2013) for the cross-sectional datasets and by Van der Weide and Milanovic (2018) in the case of US. The negative posterior co-efficient on the rule of law is in line with the prediction by Perotti and Volpin (2007) and is sole variable indicating the importance of institutions posited in Acemoglu (2003), Acemoglu and Robinson (2015). Equipment investment (machinery) may channel the resources to the bottom part of the income distri-bution through increase long-term growth rates and upward pressure on wages.

Figure 4.3: PIPs with different inequality measures
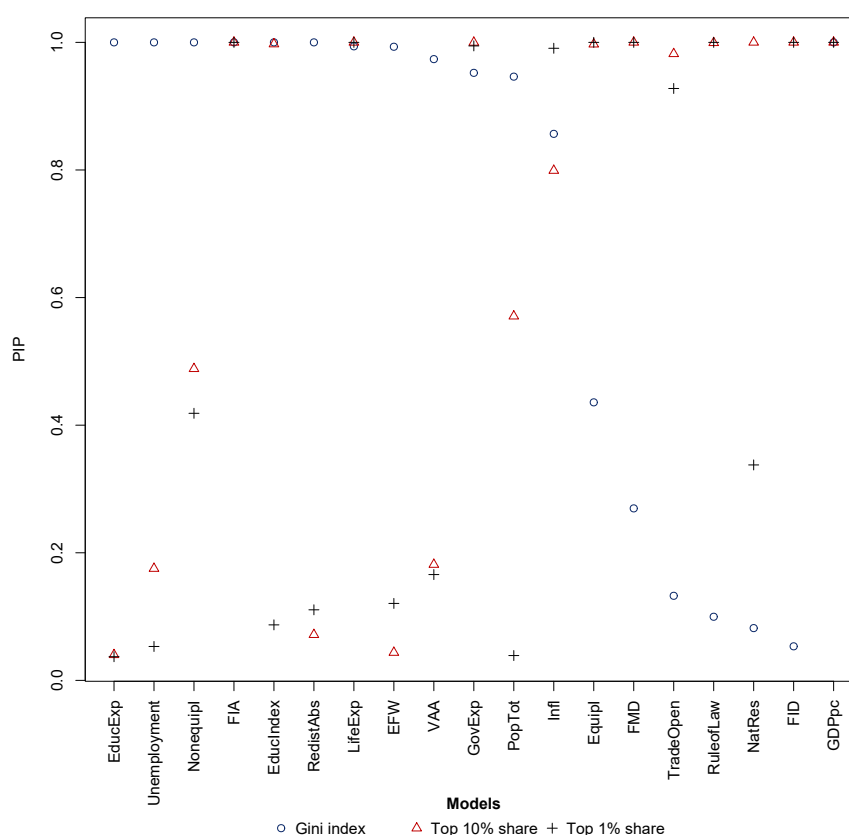
Note: The comparison only shows variables which show PIP > 0.9 in at least one of the models.

The results using the Top 1% share for top regressors differs in the drop of PIPs for natural resource rents, and education attainment. We hypothesize that natural resource rents might redistribute the share of income from the top decile to the rest of the distribution without actually affecting the share of the income going to the very top. The top 1% income earners might well be among the ones enjoying capital rents from the country resources. While education appears to have equalizing income effect for the lower part of the

Figure 4.4: PIPs for different top income shares with baseline priors
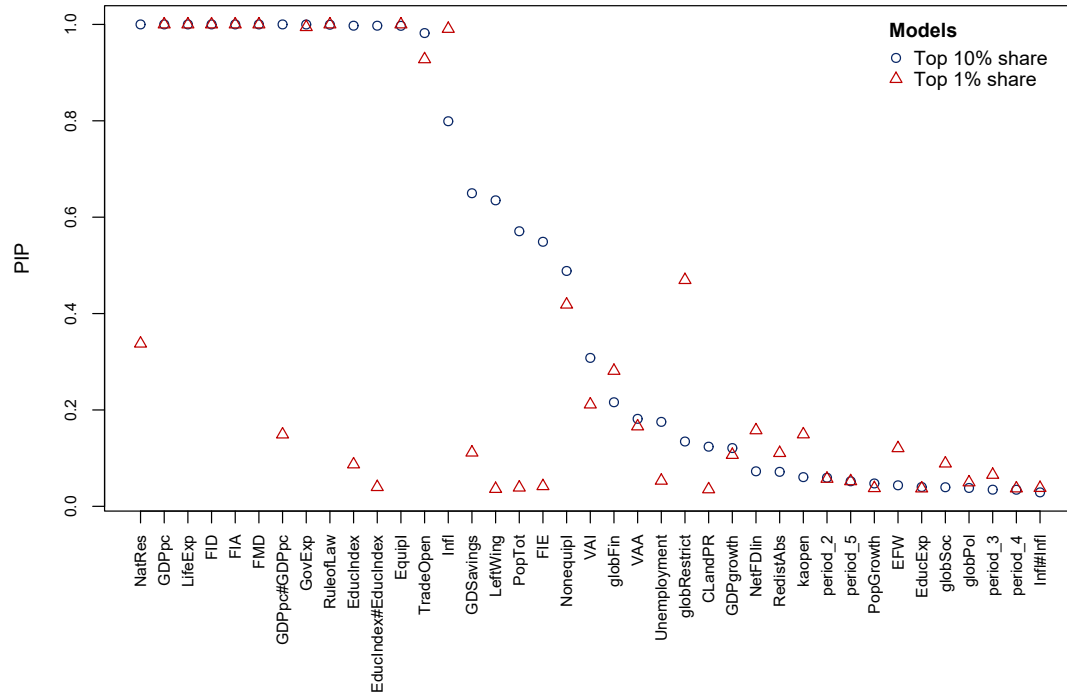
distribution, it is reasonable that it wears out for the very top income earners in the distribution. Figure 4.4 depicts comparison of inclusion probabilities of all variables considered in the estimation for the Top 10% share and Top 1% share.

4.3.3   Robustness checks

We perform robustness checks for all three specifications employing alternative model priors[12]. We choose random and dilution priors to address prior model size concentrated around the mean number of potential regressors and correlation among them by each of the model priors, respectively.

The alternative priors influence the results similarly in all three specifications. The random mode prior decreases PIPs for the regressors as it generally prefers smaller models. Nevertheless, the results are only marginally effected for Gini coefficient as well as the top income shares with a few exception of education index in the case of Top 10% share and trade openness for both top income shares. The use of dilution model prior which penalizes the models with highly correlated regressors, we see more significant differences. Above

---

[12]We also perform robustness checks using alternative hyperparameter g and Markov-chain samplers, but these do not affect our results.

Table 4.5: BMA, baseline results. Dependent variable Top 1% share, 394 observations.

	PIP	Post Mean	Post SD
Rule of law	1.00	-0.17039	0.04688
GDP per capita	1.00	0.48163	0.29090
Life expectancy	1.00	-0.45605	0.06980
Equipment investment	1.00	-0.19727	0.05526
Financial institutions depth	1.00	0.16380	0.05689
Access to financial institutions	1.00	-0.25945	0.06419
Financial markets depth	1.00	0.15454	0.04989
Government expenditures	0.99	0.11633	0.04718
Inflation	0.99	0.11773	0.04922
Trade openness	0.93	0.10374	0.05711
Restrictions on globalization	0.47	0.03804	0.05418
Non-equipment investment	0.42	0.03197	0.05001
Natural resources rents	0.34	-0.02182	0.04037
Financial globalization	0.28	-0.02001	0.04269
Value added in industry	0.21	-0.01389	0.03634
Value added in agriculture	0.17	-0.00969	0.03053
Net FDI (% GDP)	0.16	-0.00730	0.02401
Chinn-Ito index	0.15	0.00828	0.02797
GDP per capita sq.	0.15	-0.08401	0.28484
Economic freedom	0.12	-0.00945	0.03762
Gross domestic savings	0.11	0.00634	0.02688
Redistribution	0.11	0.00495	0.02085
GDP growth	0.11	-0.00504	0.02208
Social globalization	0.09	-0.00626	0.03233
Education index (UN)	0.09	-0.01003	0.07309
Unemployment	0.05	0.00131	0.01287
Political globalization	0.05	0.00137	0.01473
Financial institutions efficiency	0.04	-0.00070	0.01024
Education index sq.	0.04	0.01380	0.07857
Total population	0.04	-0.00060	0.01484
Inflation sq.	0.04	0.00053	0.01828
Population growth	0.04	0.00020	0.00844
Education expenditures	0.04	-0.00002	0.00935
Left-wing orientation	0.04	-0.00028	0.00843
Civil liberties & political rights	0.04	0.00009	0.00846

all, the quadratic terms show very low inclusion probabilities. That is not surprising since they are correlated with their original values. This irrelevance of quadratic terms is universal across inequality measures and we may argue that it is due to the construction of the concerned variables. While the PIPs for other regressors remain similar to the baseline in the case of top income shares, for the Gini index of overall income inequality, we observe some regressors which are now penalized by the dilution prior. Taking the set of the important regressors in the baseline specification, we observe drop in the inclusion probability

Figure 4.5: Robustness checks with alternative model priors, Gini co-
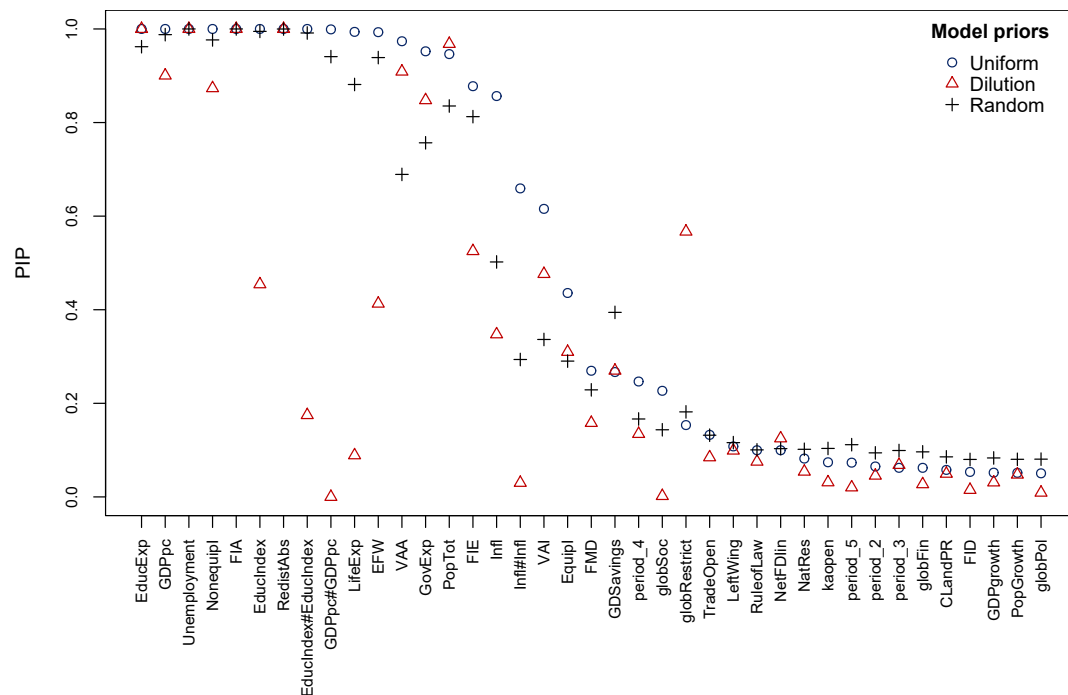efficient

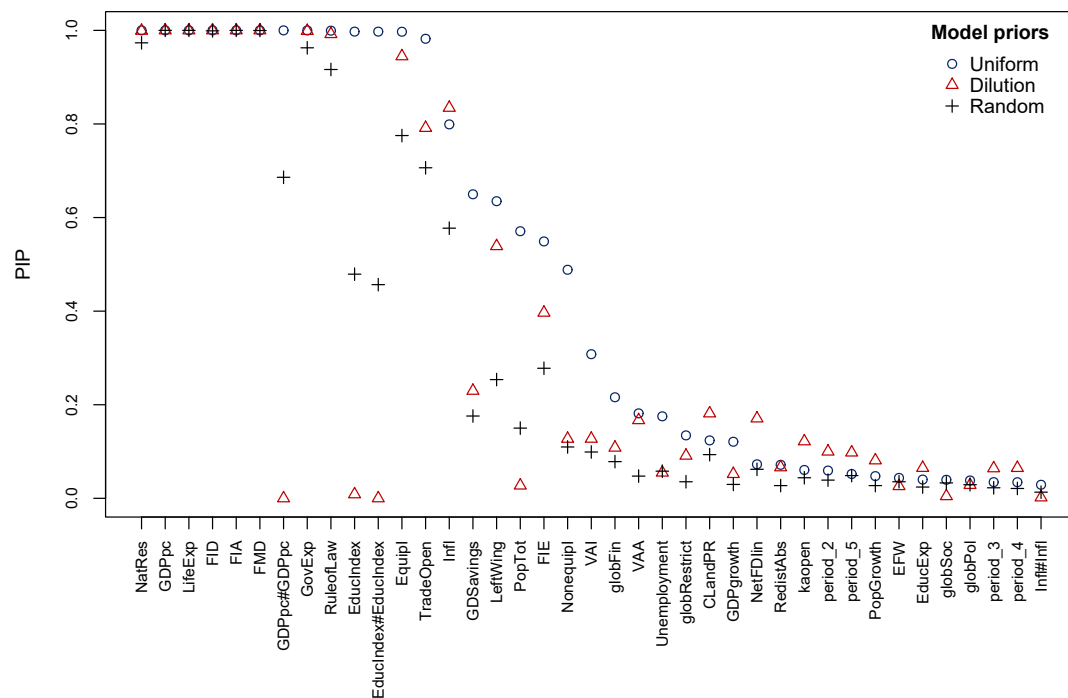Figure 4.6: Robustness checks with alternative model priors, Top 10%
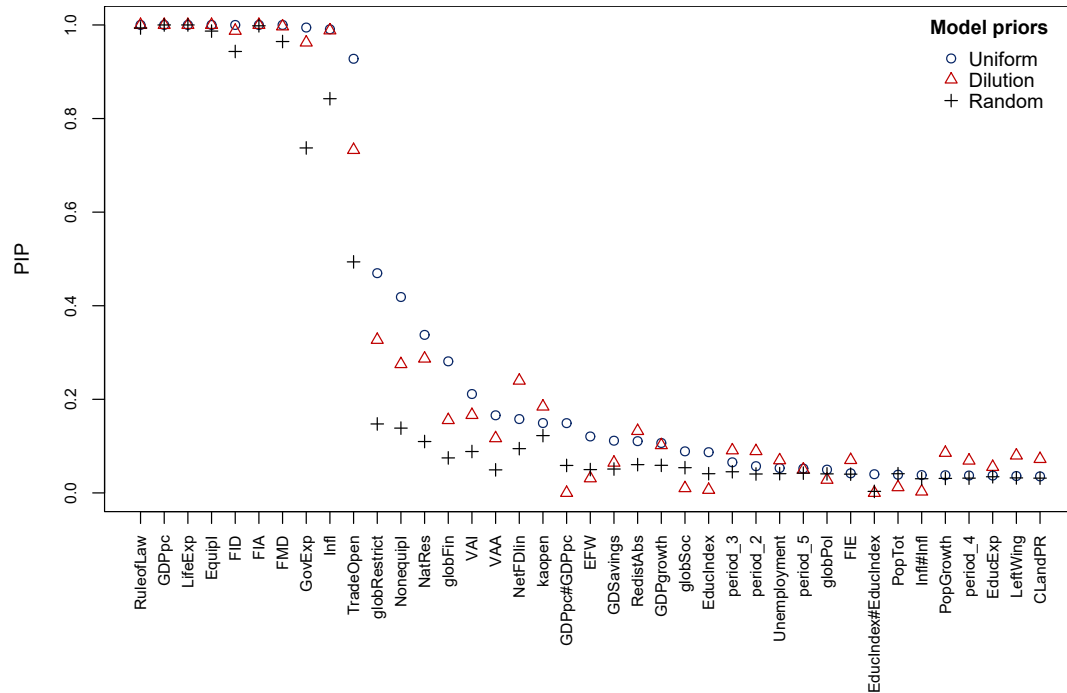share

Figure 4.7: Robustness checks with alternative model priors, Top 1% share

for education index, life expectancy, and economic freedom. Given high correlations among the set of regressors, this is not surprising and allows to narrow down the number of regressors robustly associated with income inequality.

4.4   Conclusion

In the paper, we explore the robust determinants of income inequality with a special attention given to indicators of financial development. We choose financial indicators that reflect the access, efficiency, and size of financial markets and institutions. We believe that the detailed indicators provide better proxies for the functions of finance - screen investment opportunities, monitor the debtors who were provided funding, as well as pooling and management of risk. We allow for model uncertainty by employing BMA and examine a number of other potential determinants of income inequality.

We show that financial development has complex relationship on income distribution. While access to finance has a universally inequality decreasing effect, the larger size of financial markets and financial institutions associates with higher top income shares, irrelevant for the Gini coefficient of the in-

come distribution. This finding suggests that the size of financial markets also equalizes the income among the first 9 deciles.

We find a few other important covariates for income inequality. Education, redistribution, and changing demographic structure seem to be linked with lower income inequality. On the contrary, unemployment, investment other than machinery, economic freedom - ease of pursuing economic opportunities, and inflation all positively relate to income inequality. As in the case of financial indicators, we find that the link could be more complex. When looking at the top income shares, some of the covariates (education, unemployment, redistribution, and economic freedom) cease to be relevant, while some other (trade openness, rule of law, and machinery investment) seem to matter.

The results we present warrant caution in drawing quick conclusions on the matter of income inequality determinants. While finance, technology, and trade likely affect the distributional outcomes, it can have varying influence on different parts of the income distribution.

References

Acemoglu, D. (2003). Cross-country inequality trends. *The Economic Journal*, *113*(485), F121–F149.

Acemoglu, D., & Robinson, J. A. (2015). The rise and decline of general laws of capitalism. *Journal of Economic Perspectives*, *29*(1), 3–28.

Alvaredo, F., Atkinson, A., Chancel, L., Piketty, T., Saez, E., Zucman, G., Et al. (2016). *Distributional national accounts (dina) guidelines: Concepts and methods used in wid. world* (Working paper No. 2). WID.world.

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

Anderson, E., Jalles D'Orey, M. A., Duvendack, M., & Esposito, L. (2017). Does government spending affect income inequality? a meta-regression analysis. *Journal of Economic Surveys*, *31*(4), 961–987.

Banerjee, A. V., & Newman, A. F. (1993). Occupational choice and the process of development. *Journal of Political Economy*, *101*(2), 274–298.

Beck, T., Demirgüç-Kunt, A., & Levine, R. (2007). Finance, inequality and the poor. *Journal of Economic Growth*, *12*(1), 27–49.

Beck, T., Levine, R., & Levkov, A. (2010). Big bad banks? the winners and losers from bank deregulation in the united states. *The Journal of Finance*, *65*(5), 1637–1667.

Braun, M., Parro, F., & Valenzuela, P. (2019). Does finance alter the relation between inequality and growth? *Economic Inquiry*, *57*(1), 410–428.

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

Dabla-Norris, E., Kochhar, K., Suphaphiphat, N., Ricka, F., & Tsounta, E. (2015). *Causes and consequences of income inequality: A global perspective* (Staff Discussion Note No. 15/13). International Monetary Fund.

Deaton, A. (2013). *The great escape: Health, wealth, and the origins of inequality.* Princeton University Press.

de Haan, J., & Sturm, J.-E. (2017). Finance and income inequality: A review and new evidence. *European Journal of Political Economy*, *50*, 171–195.

Delis, M. D., Hasan, I., & Kazakis, P. (2014). Bank regulations and income inequality: Empirical evidence. *Review of Finance*, *18*(5), 1811–1846.

Demirgüç-Kunt, A., & Levine, R. (2009). Finance and inequality: Theory and evidence. *Annual Review of Financial Economics*, *1*(1), 287–318.

Evans, D. S., & Jovanovic, B. (1989). An estimated model of entrepreneurial choice under liquidity constraints. *Journal of Political Economy*, *97*(4), 808–827.

Feldkircher, M., & Zeugner, S. (2012). The impact of data revisions on the robustness of growth determinants – "a note on determinants of economic growth: Will data tell?". *Journal of Applied Econometrics*, *27*(4), 686–694.

Frost, J., & van Stralen, R. (2018). Macroprudential policy and income inequality. *Journal of International Money and Finance*, *85*, 278–290.

Fuest, C., Peichl, A., & Siegloch, S. (2018). Do higher corporate taxes reduce wages? micro evidence from germany. *American Economic Review*, *108*(2), 393–418.

Furceri, D., & Ostry, J. D. (2019). Robust determinants of income inequality. *Oxford Review of Economic Policy*, *35*(3), 490–517.

Galor, O., & Moav, O. (2004). From Physical to Human Capital Accumulation: Inequality and the Process of Development. *The Review of Economic Studies*, *71*(4), 1001–1026.

Galor, O., & Zeira, J. (1993). Income distribution and macroeconomics. *The Review of Economic Studies*, *60*(1), 35–52.

Gilens, M., & Page, B. I. (2014). Testing theories of american politics: Elites, interest groups, and average citizens. *Perspectives on Politics*, *12*(3), 564–581.

Gimet, C., & Lagoarde-Segot, T. (2011). A closer look at financial development and income distribution. *Journal of Banking & Finance*, *35*(7), 1698–1713.

Goderis, B., & Malone, S. W. (2011). Natural resource booms and inequality: Theory and evidence. *The Scandinavian Journal of Economics*, *113*(2), 388–417.

Goldin, C. D., & Katz, L. F. (2009). *The race between education and technology*. Harvard University Press.

Goldstein, J. R., & Lee, R. D. (2014). How large are the effects of population aging on economic inequality? *Vienna Yearbook of Population Research*, *12*, 193–209.

Greenwood, J., & Jovanovic, B. (1990). Financial development, growth, and the distribution of income. *Journal of Policical Economy*, *98*, 1076–1107.

Gwartney, J., Lawson, R. A., & Hall, J. C. (2017). *Economic freedom of the world: 2017 annual report* (tech. rep.). Fraser Institute.

Hamori, S., & Hashiguchi, Y. (2012). The effect of financial deepening on inequality: Some international evidence. *Journal of Asian Economics*, *23*(4), 353–359.

Hasan, I., Horvath, R., & Mares, J. (2020). Finance and wealth inequality. *Journal of International Money and Finance*, forthcoming.

Jauch, S., & Watzka, S. (2016). Financial development and income inequality: A panel data approach. *Empirical Economics*, *51*(1), 291–314.

Jaumotte, F., Lall, S., & Papageorgiou, C. (2013). Rising income inequality: Technology, or trade and financial globalization? *IMF Economic Review*, *61*(2), 271–309.

Kim, D.-H., & Lin, S.-C. (2011). Nonlinearity in the financial development–income inequality nexus. *Journal of Comparative Economics*, *39*(3), 310–325.

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

Kunieda, T., Okada, K., & Shibata, A. (2014). Finance and inequality: How does globalization change their relationship? *Macroeconomic Dynamics*, *18*(5), 1091–1128.

Law, S. H., & Singh, N. (2014). Does too much finance harm economic growth? *Journal of Banking & Finance*, *41*, 36–44.

Ley, E., & Steel, M. F. (2009). On the effects of prior assumptions in bayesian model averaging with application to growth regression. *Journal of Applied Econometrics*, *24*, 651–674.

Naceur, S. B., & Zhang, R. X. (2016). *Financial development, inequality and poverty: Some international evidence* (Working Paper No. 16/32). International Monetary Fund.

Nolan, B., Richiardi, M. G., & Valenzuela, L. (2019). The drivers of income inequality in rich countries. *Journal of Economic Surveys*, *33*(4), 1285–1324.

OECD. (2011). *Divided we stand: Why inequality keeps rising*. OECD Publishing.

Perotti, E., & Volpin, P. (2007). *Investor protection and entry* (Discussion Paper No. 07–006/2). Tinbergen Institute.

Roine, J., Vlachos, J., & Waldenström, D. (2009). The long-run determinants of inequality: What can we learn from top income data? *Journal of Public Economics*, *93*(7), 974–988.

Solt, F. (2019). *Measuring income inequality across countries and over time: The standardized world income inequality database* [SWIID Version 8.0, February 2019]. SWIID Version 8.0, February 2019.

Svirydzenka, K. (2016). *Introducing a new broad-based index of financial development* (Working Paper No. 16/5). International Monetary Fund.

Tan, H.-B., & Law, S.-H. (2012). Nonlinear dynamics of the finance-inequality nexus in developing countries. *The Journal of Economic Inequality*, *10*(4), 551–563.

Townsend, R. M., & Ueda, K. (2006). Financial deepening, inequality, and growth: A model-based quantitative evaluation. *The Review of Economic Studies*, *73*(1), 251–293.

Van der Weide, R., & Milanovic, B. (2018). Inequality is bad for growth of the poor (but not for that of the rich). *The World Bank Economic Review*, *32*(3), 507–530.

Appendix

4.A   The composition of financial indicators

Table 4.6: Underlying Components of Financial Development Indicators

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

4.B   Dataset description

Table 4.7: List of variables

Variable	Definition (+ optional comments)	Source
GiniNet	Aftertax Gini index based on distribution of income (The Standardized World Income Inequality Database).	Solt (2019)
GiniMarket	Before-tax Gini index based on distribution of income (The Standardized World Income Inequality Database).	Solt (2019)
Top10share	Share of income going top decile of the distribution.	WID
Top1share	Share of income going top percentile of the distribution.	WID
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)
GDPpc	Level of GDP per capita	WB
NatRes	Total natural resource rents are the sum of oil rents, natural gas rents, coal rents (hard and soft), mineral rents, and forest rents.	WB
PopGrowth	Annual population growth 1980-2009	WB
GovExp	General government final consumption expenditure (formerly general government consumption).	WB
NNSavings	Net national savings (gross national savings less the value of consumption of fixed capital, % GNI).	WB
EducExp	Education expenditure refers to the current operating expenditures in education, including wages and salaries and excluding capital investments in buildings and equipment..	WB
Infl	Inflation as measured by the consumer price index.	WB
VAA	Agriculture, forestry, and fishing value added (% GDP).	WB
VAI	Industry value added (% GDP).	WB
GFCF	Gross fixed capital formation (% of GDP).	WB
NetFDI	Foreign direct investment, net inflows (% of GDP).	WB
GDPgrowth	Annual growth of GDP.	WB

LifeExp	Life expectancy at birth.	WB
LabForce	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.	WB
RuleOfLaw	Rule of law estimate	WB
CLandPR	Average of index for civil liberties and political rights	Freedom House
ChinnIto	Chinn-Ito index of financial openness.	Chinn-Ito
LeftWing	Dummy equal to 1 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)
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)
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)