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Three Essays on Financial Development

Dissertation thesis

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Abstract

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Abstrakt

Nutnou součástí práce je anotace, která shrnuje význam práce a výsledky v ní dosažené. Anotace práce by neměla být delší než 200 slov a píše se v jazyce práce (tj. česky, slovensky či anglicky) a v překladu (tj. u anglicky psané práce česky či slovensky, u česky či slovensky psané práce anglicky). Anotace práce by neměla být delší než 200 slov a píše se v jazyce práce (tj. česky, slovensky či anglicky) a v překladu (tj. u anglicky psané práce česky či slovensky, u česky či slovensky psané práce anglicky). V abstraktu by se nemělo citovat.

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Acronyms

BIC Bayesian Information Criterion
BMA Bayesian Model Averaging
BRIC Bayesian Risk Inflation Criterion
CBF Conditional Bayes Factor
CSWD Credit Suisse Wealth Databook
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
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
UIP Unit Information Prior
UK United Kingdom
US United States
WB World Bank
WID World Inequality Database

Chapter 1

Introduction

There goes the general summary.

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.

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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 previous 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 Cihak 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 Cihak 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.

This paper 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 4. We provide the regression results in section 5. The conclusions are presented in section 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 depends 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 variables used as proxies for the depth of the financial sector are total liquid liabilities 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 remains unclear. For instance, Cihak et al. (2013) illustrate that private bond market capitalization represents a substantial share of the total securities market 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 development. 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. Cihak 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:

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

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:

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

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 section 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:

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

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:

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

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:

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

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 $g \to \infty$, $\beta_i \to \beta_i^{OLS}$. 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 $g \to \infty$. For details on hyper-g, see Liang et al. (2008).

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

Model Priors

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

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

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

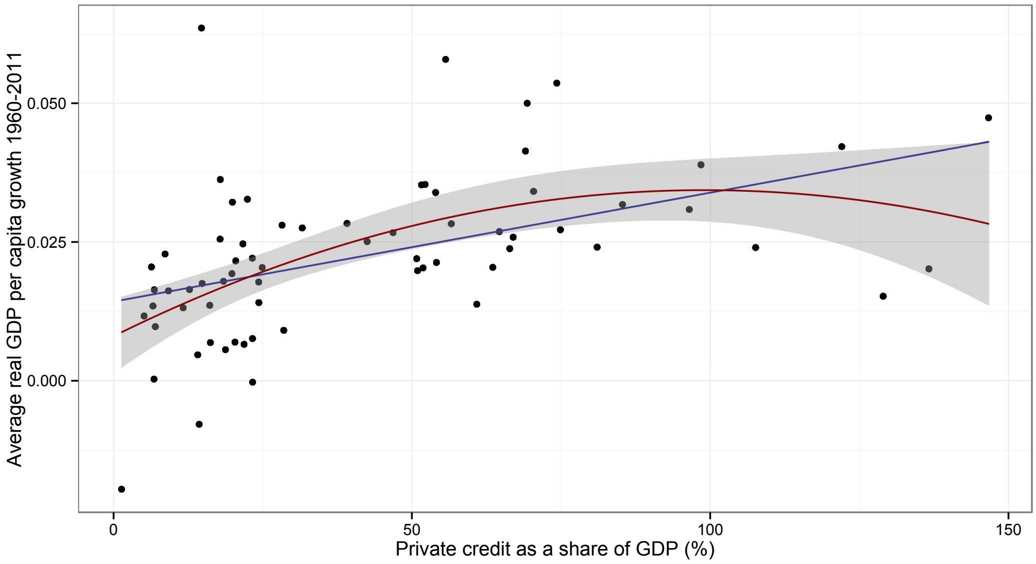

Figure 2.1: Private credit and growth, 1960-2011

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 (2012). 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 (2012), 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

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

the BRIC prior and focus on alternative options for parameter priors in our robustness checks.

The birth-death MC^3 sampler described in section 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

[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.

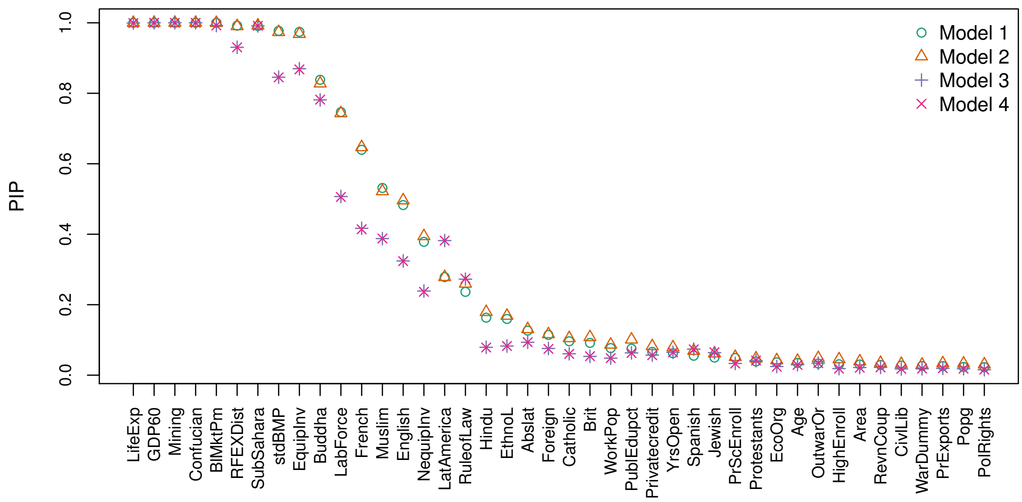

Figure 2.2: Model comparison with private credit, Model 1=hyper-g,birth-death; Model 2=hyper-g,reverse-jump; Model 3=UIP,birth-death; Model 4=UIP,reverse-jump

15.05 and the PMP correlation between analytical and MC^3 sampler likelihood 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. Cihak 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

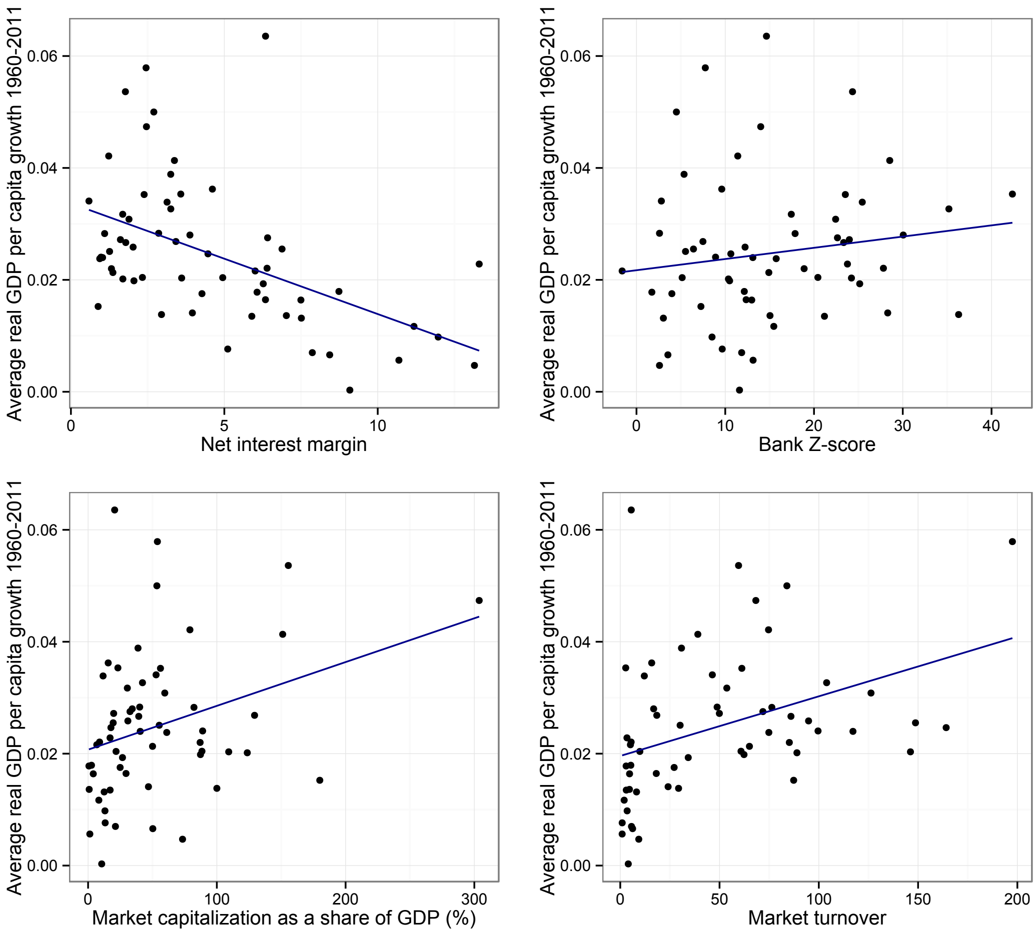

Figure 2.3: Financial indicators and growth

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 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

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

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, 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.

[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
Bayesian model averaging

	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

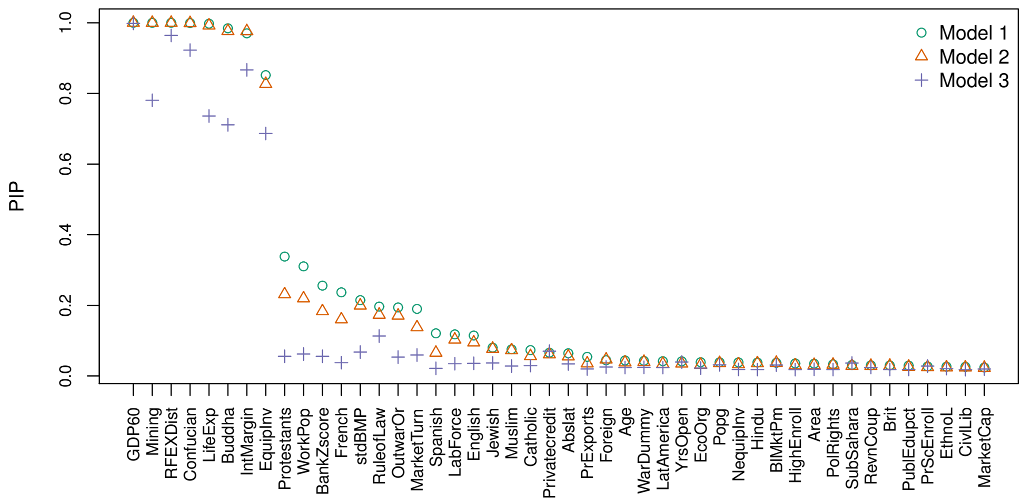

Figure 2.4: Model comparison with all financial indicators 1960-2011, priors Model 1=hyper-g, uniform model prior; Model 2=UIP, uniform model prior, Model 3=hyper-g, dilution model prior

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 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.

[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.

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 relationship 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.

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.

[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 2.6: 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

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

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.

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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

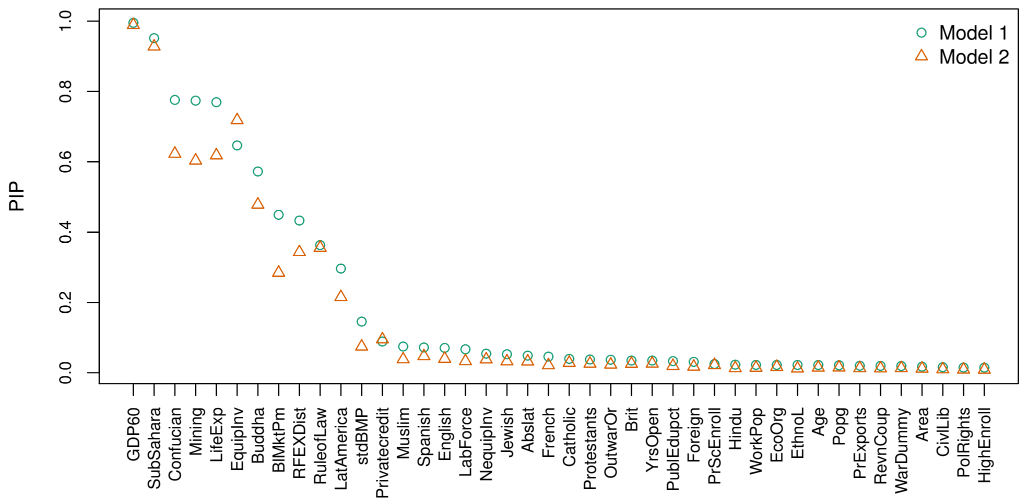

Figure 2.5: Model comparison with private credit, Model 1=hyper-g, random model prior; Model 2=UIP, random model prior

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 suggested by Ley and Steel (2007) (LS) for decisive (dis)jointness. Nevertheless, jointness statistics for some of the pairs suggest very strong jointness (e.g. market capitalization and private credit). Another way of constructing jointness statistic has been developed by Doppelhofer and Weeks (2009) (DW). Regarding 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 similar factors and thus be mutually replaceable in the estimation process, they should also exhibit the same importance regarding economic growth if considered 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 variable 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 inequality.

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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, 2018). What accounts for these (dramatic) differences in wealth inequality across countries? Is it different degrees of redistribution, financial development, globalization, technological progress or economic development? Alternatively, are there possibly some other factors? Although extensive progress has been made regarding the measurement of wealth inequality (Alvaredo et al., 2013; Davies et al., 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 paper 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 Section 3.A in the Appendix.

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

[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.

eventually turns negative if individual wealth is sufficiently greater than labor earnings. In other words, the basic setup implies negative saving rates for the rich. It also overstates the fraction of the population that does not save at all. These features of the model are in contrast with the data in United States (US), in which we observe high saving rates for the rich, and the share of agents without savings is very small (Nardi & 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, 2018).

Private wealth is of utmost importance for individual decisions regarding investment, especially in an environment with asymmetric information and binding credit constraints. The consequences of the distribution of wealth are important in theories explaining the different speeds of development across countries (Roine & 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 investment 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.

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

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 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 3.19 in the Appendix.

We focus on financial development and its effect on the distribution of wealth within the economy. There are more than 100 indicators available in GFDD by the World Bank (WB), capturing specific features of financial development. Building on the framework by Cihak et al. (2013), who describe four main dimensions of financial systems – depth, efficiency, stability, and access – Svirydzenka (2016) constructs aggregate indexes representing these dimensions

[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.

using the most densely available series in the database. Furthermore, GFDD allows for not only distinguishing between the different dimensions of financial development but also ascribing these dimensions to the banking sector and financial markets separately. Except for stability and access, for which we only control for variables representing the banking industry due to data limitations, we take advantage of this distinction in our analysis.

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 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.

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 the top decile and top percentile of the distribution is available for other met-

[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.

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

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)

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.

rics. 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.

Table 3.3: Finance and Wealth Inequality: Correlations

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

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

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

(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 Section 3.H 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

mations. For more details about the estimated regressions for financial assets, nonfinancial assets, and liabilities, we refer to Davies et al. (2017).

& Zeugner, 2009; Liang et al., 2008). In the following subsections, we present the prior structure and support our choices.

Parameter Priors

We use Zellner's g prior structure, which is a common approach in the literature. The prior structure assumes that the priors on the constant and error variance from equation 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).

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[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 $\frac{2}{a}$

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

Model Priors

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

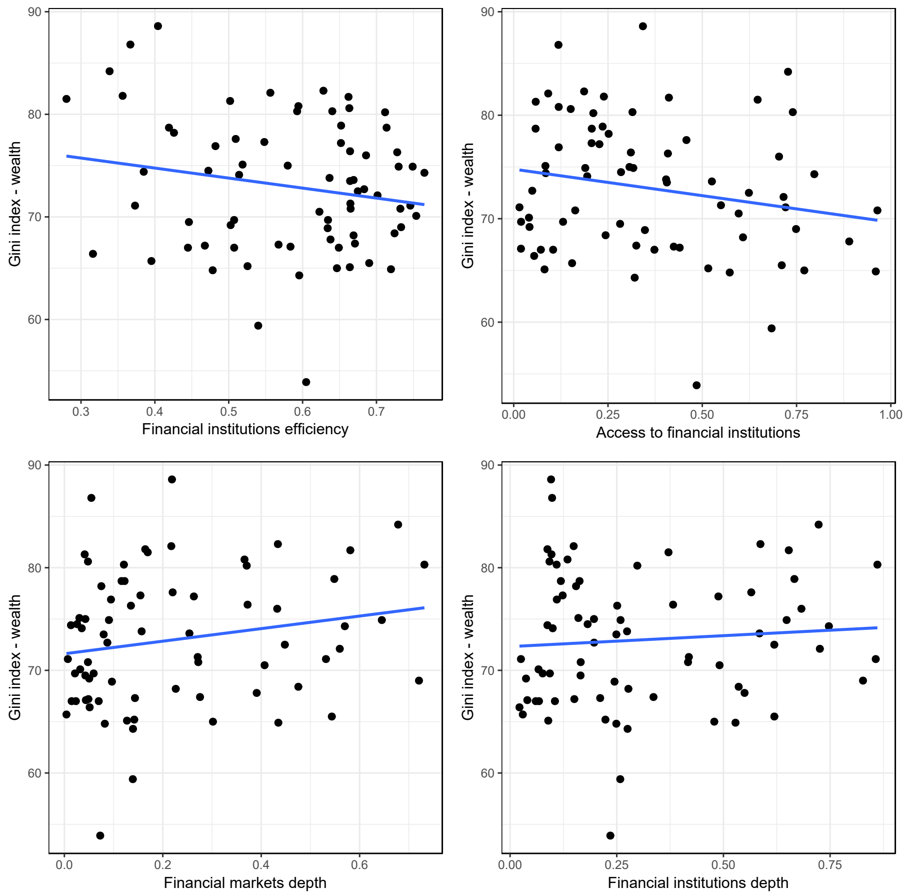
In this section, we first present several scatter plots to visualize the relations between financial development indicators and wealth inequality. Second, we present BMA results regarding the determinants of wealth inequality, third, we present the results for restricted samples of high- / low- income 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 â€špositiveâ€t evidence for the effect, in case of PIP higher than 95%, but

Figure 3.1: Finance and Wealth Inequality



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. 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 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

[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 3.18 in the Appendix.

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

[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.

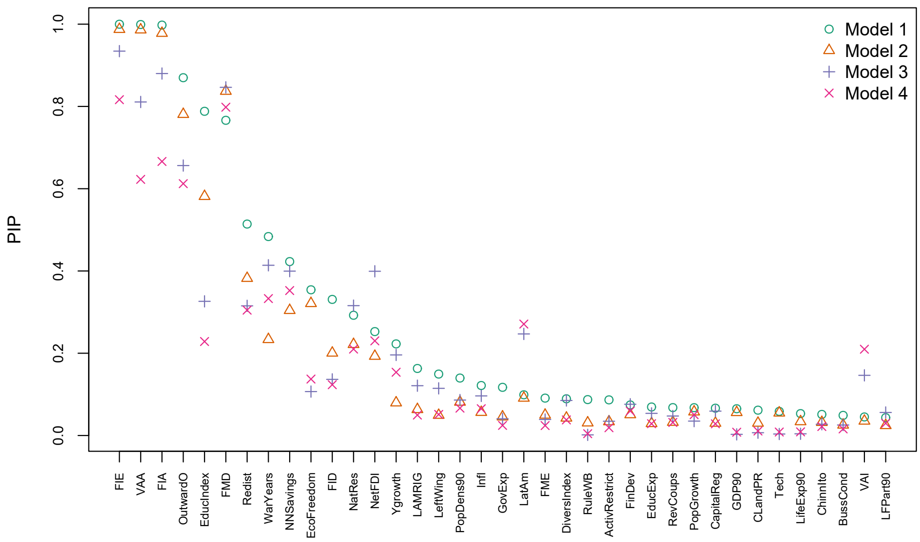
conflicts involving a single or small number of countries. These conflicts have adverse macroeconomic effects, undermine the rule of law, cause violent confiscation of private property by militias and reduce trust in society, especially if these conflicts occur repeatedly (Bircan et al., 2017). Bircan et al. (2017) study the effect of internal violent conflicts on income inequality and also find inequality increases, but this effect is temporary, and later on, inequality falls slowly back to the steady state.

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



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

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 of agriculture sector in developing countries. Wars matter both for low-income

[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 3.4 greater than 0.5. The results are largely the same and are available upon request.

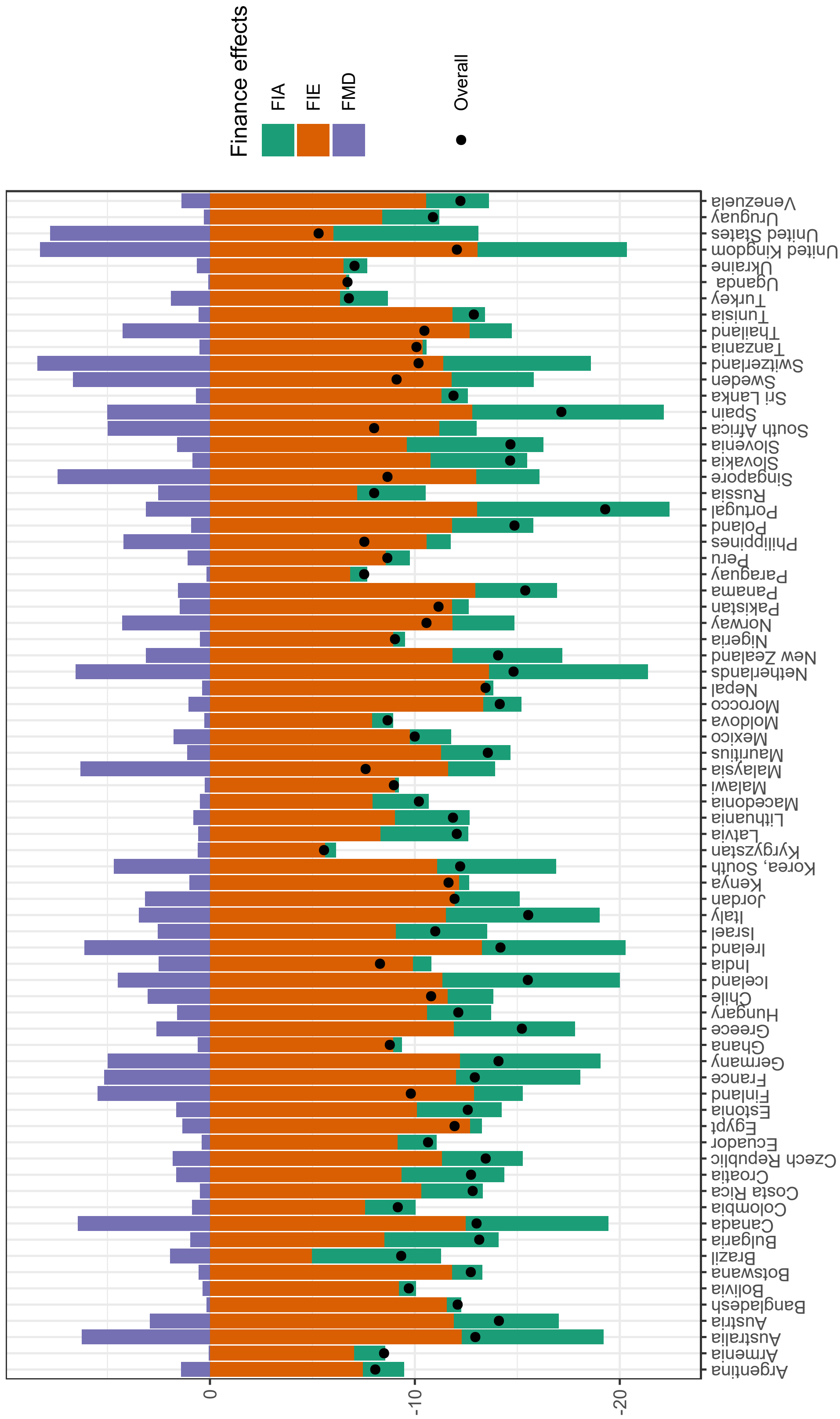


Figure 3.3: Effects of individual financial development components on inequality

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 of the regressions are 35.43 and 19.95 for FIA and FID, respectively. Both val-

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

ues 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 uncertainty. This uncertainty arises from the lack of an encompassing model of

[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.

wealth inequality, which would dictate the exact regression specification to be estimated. As a side effect, using BMA, we can examine a large number of possible determinants of wealth inequality within a unifying framework. Therefore, we examine how different economic, financial, regulatory, political, social, and institutional variables affect wealth inequality.

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

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

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

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

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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, expected effects

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	-0.11	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

Table 3.15: Expected effects of the explanatory variables

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

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

Table 3.16: 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 3.17: 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 3.18: 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

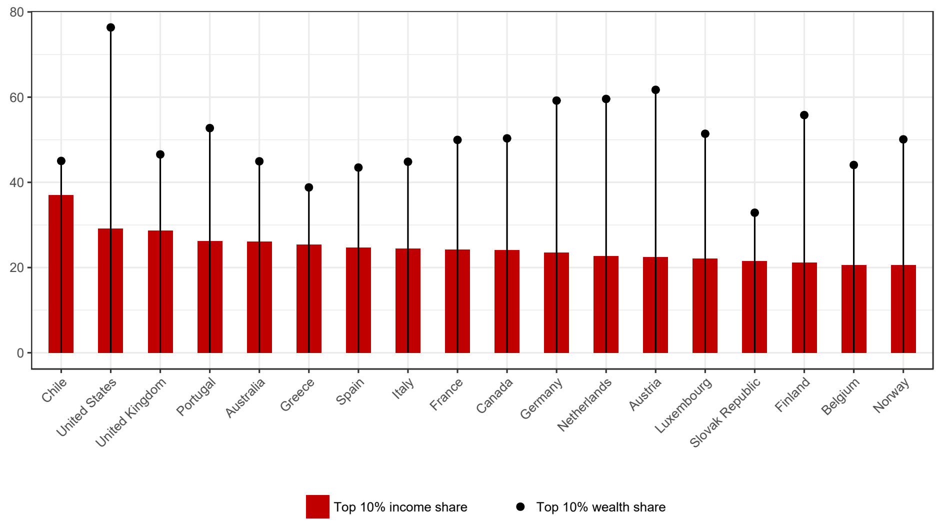
Table 3.19: List of variables

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



Note: Source: Author based on the OECD

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 section 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:

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

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

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

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):

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

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

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

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:

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

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:

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

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.