What Kind of Finance Matters for Growth? A Bayesian Model Averaging Evidence*

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December 27, 2014

Preliminary

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. Previous literature largely focuses on financial indicators assessing the financial depth of banks and stock markets. We examine these indicators jointly with the newly developed indicators assessing the stability and efficiency of financial markets. Subject to a number of sensitivity checks, we find that the bank efficiency is robustly related to long-term growth using our global sample. Other financial indicators assessing financial depth or financial stability matter less.

Keywords: Finance, Growth, Bayesian Model Averaging

JEL Codes: C11, G10, O40

*We acknowledge the support from the Grant Agency of the Czech Republic P402/12/G097. The views expressed here are those of authors and not necessarily those of the Czech Ministry of Finance or Bank of Finland. Email contacts: roman.horvath@gmail.com

1 Introduction

Numerous studies have investigated the effect of financial development on economic growth and predominantly concluded there is causal and positive link from finance to growth. Among others, King and Levine (1993); Levine and Zervos (1998); Atje and Jovanovic (1993) established grounds for modern research on this topic. Nevertheless, opposing views claim that financial sector captures scarce resources from the economy (Tobin, 1984; Bolton et al., 2011; Kneer, 2013) and also contributes to higher exposure and vulnerability of economic systems to crises, severely burdening real sector in the periods of unrest (Kindelberger, 1978; Minsky, 1991; Stiglitz, 2000). This dilemma has recently drawn more attention again owing to the financial crisis of 2007-2008. The crisis illustrated how bloated financial systems can indirectly waste resources by their poor allocation, encouraging speculation, and deterring investments (Law and Singh, 2014). Moreover, the conclusions referring to diminishing and eventually negative returns to financial development have nowadays become increasingly frequent in the literature (Arcand et al., 2012; Cecchetti and Kharroubi, 2012; Law and Singh, 2014). Consequently, this highlights the importance of financial sector and provokes extensive debate among the policy-makers.

This paper evaluates the finance-growth nexus but differs from previous research by employing Bayesian model averaging. This method 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 (Fernandez et al., 2001; Sala-I-Martin et al., 2004; Durlauf et al., 2008). In addition, this paper examines more financial indicators than previously examined. Importantly, previous research, including the studies implying that too much finance harms growth, largely focus on the measures of financial depth such as credit to GDP ratio. We differ from previous research in examining jointly whether it is depth, stability or efficiency of financial markets (or all of them), which matters for growth. This way we can unify and re-examine previous studies on finance-growth nexus, which show that a) finance is conducive to growth, b) but too much finance is not and c) financial instability has a negative consequences for growth.

Economic theory outlines the link of finance to growth by stressing financial sector's role in generating information, exerting corporate governance, ameliorating risk, pooling savings, and easing exchange (Ang, 2008). However, these concepts are difficult to operationalize in the empirical research and there is no universal agreement on the measurement of financial development. Even though the measurement of financial development is complex, the researchers typically used only the variables capturing the financial depth such as credit to GDP ratio or stock market capitalization to assess the degree of financial development. The financial indicators assessing the degree of financial access, financial stability or the efficiency of financial industry have been largely ignored. The newly developed Global Financial Development Database (GFDD), represents a significant improvement in this respect and provides a a comprehensive set of financial indicators reflecting different functions and characteristics of financial sector. Apart from depth, it reports the measures of the efficiency, stability, and access to financial markets. Although the data availability remains restrictive, we provide extension to the existing literature by including these different dimensions of financial sector into our regression analysis. Specifically, the indicators we use represent depth, stability, and efficiency of banking sector and stock markets as defined by Cihak et al. (2013). In addition to GFDD, we employ the commonly used dataset on the long-term growth by Fernandez et al. (2001) encompassing more than 40 explanatory variables capturing various economic, political, geographical or institutional indicators.

One of the issues innate to empirical studies on growth is the 'model uncertainty' (Fernandez et al., 2001; Durlauf et al., 2008). A large number of determinants arises from plentiful theories on the subject of economic growth and results in high uncertainty about true growth model. To rigorously address this uncertainty, we employ BMA methodology. To put it intuitively, BMA estimates different combinations of explanatory variables, and subsequently weights the coefficients by various measures of model fit. BMA also conveniently limits the concerns regarding omitted variable bias that is usually abstracted from in the empirical work on finance and growth. Such ignorance may presumably result in inconsistent estimates of the relationship as documented by Garretsen et al. (2004). BMA is capable of evaluating many possible regressors and estimating their posterior inclusion probability (PIP), i.e. the probability that they are relevant in explaining the dependent variable, along with weighted mean and variance of their corresponding coefficients.

While it is commonly assumed that the inference goes from financial development to economic growth, some argue growing financial sector merely follows the increasing needs of real economy, or may be determined simultaneously with growth by third factors. Indeed, the quantitative survey of finance and growth literature by Valickova et al. (2015) show that the studies ignoring endogeneity are more likely to report stronger positive effect of finance on growth. Therefore, we examine the robustness of our results under specifications accounting for endogeneity. In particular, we use two stage least square (2SLS) estimation combined with BMA introduced by Durlauf et al. (2008). To the best of our knowledge, the study combining various characteristics of financial sector, rich growth dataset, and integrating model uncertainty and endogeneity is yet absent in the literature.

Using data on real economic growth in 68 countries between 1960 and 2011, we find that the bank efficiency is robustly related to long-term growth and exhibits very high PIP. The relevance of traditional variables such as credit to private sector or stock market capitalization is weaker. This result survives a series of robustness checks such as employing different sample period or addressing endogeneity. Therefore, our results highlight the measurement of financial development is crucial for the estimated effect of finance on growth. Our policy implication is that the current wave of regulatory changes of financial industry around the globe should not underestimate the importance of the efficiency of financial sector.

This paper is structured as follows. Section 2 provides the literature survey on finance and growth. Section 3 presents the data. We provide the regression results in section 4. The conclusions are given in section 5. An Appendix with additional results follow.

2 Empirical Literature on Finance and Growth

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

2.1 Empirical Evidence

Focusing on the period between 1960-1989, King and Levine (1993) show how the initial levels of different financial indicators such as the liabilities to financial sector, bank ratio, credit to non-financial private sector/total domestic credit, and credit to private sector to GDP explain the real growth in GDP per capita, capital accumulation, and efficiency of capital utilization in the following period. Atje and Jovanovic (1993) examine the stock market effects on economic growth and find that more active stock markets induce growth. The conclusions about stock market activity were subsequently confirmed by Levine and Zervos (1998), too. In addition to providing evidence on the stock market effects, they simultaneously control for banking sector development by including credit to private sector. Interestingly, both banking sector and stock markets are significant in fostering growth. This leads the authors to conclusion each of the sectors has different function in the economy providing different financial functions. Furthermore, they add that the mere size of the stock market measured by total capitalization is irrelevant to growth and what matters is specifically the activity of the stock market. Nevertheless, this link may be an outcome of an unobserved third factor stimulating both trading activity and economic growth. For instance, information about new technology may spur trading activity due to conflicting opinions about future benefits from the innovation. The subsequent economic growth is a result of technological advancement rather than greater trading volumes (Levine, 2005).

Rajan and Zingales (1998) initiate the research on the finance-growth nexus using the industry level data. Rajan and Zingales (1998) put forward that more developed financial markets decrease the cost of external capital for the firms. Indeed, they find evidence that industries relatively more dependent on external finance grow faster in the countries with better developed financial intermediaries. Besides, their results provide additional support in favor of stock market capitalization irrelevance. Building on this methodology, Claessens and Laeven (2005) arrive at similar inference using measures of bank competitiveness. 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 which posits financial development is crucial factor in alleviating financial constraints. 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) matters for growth much more than financial depth (measured by outstanding credit). Berger et al. (2004) provide an international evidence on the importance of bank efficiency for growth. Similarly, using the German data, Koetter and Wedow (2010) find that bank efficiency is positively related to growth.

Panel and time-series analyses dominantly advocate the link goes from finance 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) show the positive long-run growth effects of financial development using cointegration techniques. Christopoulos and Tsionas (2004) argues in favor of long-run causality from finance to growth and dismisses the backward channel. Fink et al. (2003) is one of the few papers investigating the relationship considering private bond markets. Peia and Roszbach (2015) revisits the causality in finance-growth nexus and show that the causality depends on the measurement and 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 banking sector. They show how the importance of bank credit to growth lessens with increasing availability of alternative debt financing options. While pointing to the 'finance-lead' growth prevail, opposing view stressing irrelevance exist. Garretsen et al. (2004) document the causal link found by Rajan and Zingales (1998) disappear when societal and legal factors are accounted for. It may be that development of financial markets simply follows growth, reflecting the needs of larger economy. After all, accounting for time and country-specific effects does not free the analyses from caveats completely. Time coverage is often short and utilizing more frequent observations, such as quarterly data, does not rightfully address the hypotheses about long-term nature of the relationship (Ang, 2008).

More recently, finance and growth literature experiences increased attention following the economic crisis of 2007-2008. The questions have been raised about possible non-linearities in finance-growth nexus, more specifically, whether the excessive levels of financial development are harmful for growth. Rousseau and Wachtel (2011) show the positive correlation between development of financial sector and economic growth is typical for period before 1990. The effect diminishes when later period is considered. More studies find evidence of inverted U-shape relationship. Financial development is conducive to growth only up to certain threshold and after that act as a drag on economic growth (Cecchetti and Kharroubi, 2012; Arcand et al., 2012; Law and Singh, 2014). Some explanations have been put forward in order to justify these findings. One of them is comparatively larger amount of credit going to households in the later stages of financial deepening. These loans generally tend to be less productive than loans to enterprises (Beck et al., 2012). Cecchetti and Kharroubi (2013) emphasize that the larger size of financial sector leads to lower total factor productivity through relatively larger merits for high-collateral/low-productivity projects, mainly in construction. Other lines of reasoning rely on Tobin's early work about finance luring talent from other sectors (Bolton et al., 2011; Cecchetti and Kharroubi, 2012; Kneer, 2013). To conclude, these recent empirical studies find that the growth enhancing effects of financial development are not guaranteed and suggest the relationship is more complex that originally thought.

2.2 Measurement of Financial Development

Levine (2005) argues that it is difficult to link empirical counterparts to theoretical research on finance and growth. The concepts such as information asymmetry, better corporate governance, risk management, pooling savings, and easing exchange are in reality difficult to measure accurately. Most commonly used indicators of financial development are those on financial depth, above all because of its widespread availability. Conventional variables used as proxies for financial sector depth are total liquid liabilities of financial sector, credit to private sector, and different measures of monetary aggregates. While the aforementioned variables depict the development of banking sector, in the case of the stock market studies, broadly employed proxies are the ratio of total market capitalization to GDP, total value traded to GDP (stock market activity ratio), and total value traded to total value of shares listed (turnover ratio). It is not clear to what extent these traditional measurements reflect the ability of financial intermediaries to exert functions assigned to them in theory. For instance, Cihak et al. (2013) illustrate that private bond market capitalization creates a substantial part of total securities market capitalization within a country. However, in 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 and Rajan, 1997). In addition, Levine (2005) notes this factor may be particularly important in countries with poor legal environment or overly regulated financial systems. All in all, there is no general agreement on appropriate measurement of financial development among researchers. Commonly, studies consider several potential indicators to assess robustness of the results but typically these indicators are proxy only for the level of financial depth (Valickova et al., 2015).

3 Data

We use the dataset from seminal paper on long-term economic growth determinants and BMA by Fernandez et al. (2001). The dataset contains 41 explanatory variables potentially 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 of various measures of economic, political, geographical, demographic, social, and cultural factors. As many of these factors may be simultaneously determined with growth, the regressors typically come from 1960 or even before to alleviate endogeneity concerns. We describe this dataset in the Appendix in a greater detail.

To this dataset we add selected financial indicators from the World Bank's GFDD. It collects information about various aspects of financial sectors around the globe. Cihak et al. (2013) introduce its content in detail and also offer an '4x2' dimensional classification of financial indicators reflecting their utility in representing depth, breadth, efficiency, and stability ('4') of both banking sector and stock market ('2'). We choose to employ several indicators on which the database is the richest. Specifically, we select:

- **Private sector credit to GDP:** domestic private credit to the real sector by deposit money banks to GDP - depth of banking sectors.
- **Stock market capitalization to GDP:** value of listed shares to GDP - depth of stock markets.
- **Net interest margin:** accounting value of banks' net interest revenue as a share of it average interest-bearing assets - efficiency of banking sector.
- **Stock market turnover ratio:** stock market value traded to total market capitalization - efficiency of stock markets.
- **Bank Z-score:** return on banks' assets plus the ratio of banks' equity and assets, divided by standard deviation of return on assets $\left(\frac{ROA+\frac{equity}{assets}}{sd(ROA)}\right)$ - stability of banking sectors.

Aforementioned dimensional distinction allows us to differentiate and compare the effect of banking sector and stock market on economic growth. In addition, unlike previous literature, we examine whether depth, efficiency and stability of financial system matters for growth.

The time and cross-country coverage of financial variables varies. Private credit to the real sector is available for majority of the countries in the dataset since 1960. On the other hand, remaining variables are typically available only from the 1980s. We average the indicator values correspondingly to selected time-period, i.e. 1960-2011 (except credit) and to their data availability. This is a standard procedure in estimating empirical long-term growth models, despite the risk of introducing endogeneity in the model and loss if information introduced by averaging over extended time periods. The benefit of averaging is a focus on long-term trends abstracting from short-term fluctuations. Given the data availability and the construction of the dataset, all financial variables except private credit are endogenous. We address the endogeneity issues in our BMA approach. Table 1 gives description statistics of individual financial indicators.

Table 1: Descriptive statistics, financial indicators

	Min	Max	Mean	Std.dev
Net interest margin	0.59	13.31	4.81	3.32
Bank Z-score	-1.61	42.35	15.62	9.97
Private credit	1.34	146.66	42.86	34.79
Market capitalization	0.67	303.77	50.56	52.84
Market turnover	0.96	197.50	48.22	47.13

4 Bayesian Model Averaging

We introduce the Bayesian model averaging in this section (Raftery et al., 1997). To illustrate the application of BMA, we begin with a traditional linear model structure:

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

where y is a dependent variable, α a constant, X is the matrix of explanatory variables, β the corresponding coefficients, and ε is a vector of normally distributed IID error terms with variance σ^2. In this linear regression framework the number of explanatory variables which could affect the dependent variable is often very large. As the form of true model is unknown, its construction often begins by including all the variables into the model. However, this yields imprecise results as the higher number of regressors increases standard errors on coefficients and results in less accurate estimation. Empirical research usually approaches this issue by sequentially eliminating least significant 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 a risk that the researcher keeps the variable although it is irrelevant or drops important variable. Koop (2003) emphasizes that the probability of making such mistake increases quickly with the number of sequences carried out. The different iterations paths may also lead towards different definitions of the model. Even if we assume the 'best' model is found through this procedure, it is rarely acceptable to only present the results from the 'best' model and disregard the results of 'second-best' models. This approach ignores the model uncertainty researcher faces when she defines the model. BMA allows to account for such uncertainty and presents a rigorous method of treating multiple models.

BMA considers all the possible combinations of X from Equation 1 and takes a weighted average of the coefficients (see also the remarks on MCMC sampler below). The substructure of the model can be captured as follows:

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

Here, the X_i is a subset of X and α, β_i corresponding coefficients. Assuming total number of possible explanatory variables is K, total number of models is equal to 2^K and $i \in [1, 2^K]$. In the model, researcher is interested in describing coefficients based on observed data. It follows from Bayes rule that

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

where $p(\beta|y, X)$ is the posterior density, $p(y, X|\beta)$ the marginal likelihood (ML) also known as the data generating process, $p(\beta)$ the prior density, and $p(y, X)$ the probability of the data. In the BMA, we essentially compare many 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 where we formally define the model by a likelihood function and a prior density, M_i depends on parameters β_i and their posterior probability can be derived as follows

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

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

4.1 Posterior model probability

The posterior model probability (PMP) is fundamental in the BMA framework as it provides the weights for averaging of model coefficients across sub-models. PMP also arises from Bayes' theorem

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

$p(y|X, M_i)$ 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 denominator is usually disregarded as it is constant over all the models in consideration. The PMP is then directly proportional to ML and prior probability. A popular practice is to set the prior probability $p(M_i \propto 1)$ to reflect the lack of knowledge about the true model.

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

The calculation of ML is discussed in detail in Section 4.4. The model prior needs to be elicited by the researcher and reflects the initial beliefs before inspecting the data.

4.2 Posterior mean

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

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

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

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

Here, $E(\beta|y, X)$ are the averaged coefficients 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 parameter in M_i as

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

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

4.3 Posterior variance

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

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

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

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

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

4.4 Marginal likelihood

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

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

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

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

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

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

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

4.5 Posterior Inclusion Probability

The standard BMA framework also reports the PIP reflecting the probability that a particular regressor is included in the 'true' model. PIP is computed as the sum of PMPs of the models including the variable k in question

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

4.6 Conditional Posterior Positivity

Interesting feature of the parameter posterior is its sign (Koop, 2003). Conditioned on the inclusion of the regressor in the model its positivity is calculated as

$$p(\beta_k \geq 0|y, X) = \sum_{i=1}^{2^K} p(\beta_{i_k}|M_i, y, X)p(M_i|y, X) \tag{16}$$

the values of conditional positivity close to 1 indicate the parameter is positive in vast majority of considered models. On the contrary, values near 0 indicate dominantly negative sing. This characteristic is very useful to asses the parameters' importance in more detail.

4.7 Priors

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

4.7.1 Parameter priors

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

Most important prior is on the regressions coefficients β_i. We assume the coefficients follow normal distribution and we have to formulate beliefs about its mean and variance before looking at the data. Conventionally, researchers assume conservative mean of 0 to reflect the lack of prior knowledge about 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

$$\beta_i|g \sim \; N(0, \sigma^2(g(X_i'X_i)^{-1}) \tag{17}$$

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

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

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

We employ with so-called UIP g prior to estimate the baseline models. Robustness of the results is then carried out by applying different model priors. In particular, we rely on selection of g by Fernandez et al. (2001), who use BRIC prior, and Feldkircher and Zeugner (2009), who suggest using model specific hyper-g prior leads to more stable posterior structure.

4.7.2 Model priors

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

$$p(M_i) = \theta^{k_i}(1 - \theta)^{K - k_i} \tag{18}$$

A popular 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 uniform model prior. Assuming different values of θ can tilt the prior model distribution to either smaller or larger sizes (see Zeugner (2011)).

We focus on models using uniform model prior following Fernandez et al. (2001) as it allows for comparison with the results of their study. However, uniform model prior tends to put more mass on intermediate model sizes. For illustration, take our dataset of 42 regressors. The expected model size is $\frac{K}{2} = 21$, but there is clearly a higher number of possible models of size 21 than 1. More specifically, there is 42 possible models of size 1, while $\binom{42}{21}$ combinations (more than half a trillion) exist for the model size of 21. Therefore, Ley and Steel (2009) propose an alternative model prior less tight around the expected model size, drawing parameter θ from Beta distribution. Their argument is this option better reflects the lack of *a priori* knowledge about the model. We use this 'random' beta binomial prior in the specifications checking the robustness of our baseline estimations.

4.8 MCMC sampler

One of the BMA limitations is the computational difficulty when the number of potential explanatory variables K is very high. Historically, this was indeed the main cause preventing researchers to apply Bayesian methods. Zeugner (2011) denotes that for small models, it is possible to enumarate all variable combinations. When $K > 25$, it becomes impossible to walk through the whole model space within reasonable time frame. In such cases, BMA utilises MC^3 samplers to approximate crucial part of the posterior model distribution containing the most likely models. BMA applies 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 new model M_j with probability

$$p_{i,j} = min\left(1, \frac{p(M_j|y, X)}{p(M_i|y, X)}\right) \tag{19}$$

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

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

Because the sampler can start off at a 'poor' model with low PMP, predefined number of initial draws, so called burn-ins, are usually dropped. The quality of the approximation can be evaluated on the basis of correlation between PMP based on analytical approach and ones from MC^3 sampler. It depends on the number of iterations (draws) and the likelihood of initial chosen model. Zeugner (2011) argues PMP correlation around 0.9 indicates a 'good degree of convergence'. In case the correlation is lower, the number of sampler iterations should be increased.

4.9 Endogeneity issues

Our dataset is constructed in the way that most regressors are exogenous except some financial indicators. To address the endogeneity of these indicators, we apply the methodology developed by Durlauf et al. (2008). The endogenous financial variables are regressed on the set of instruments in the first stage and its fitted values are used in the second stage, which is a standard BMA procedure. We acknowledge that the first stage is not fully Bayesian but it is important to note that the number of endogenous variables and instruments is rather low. In addition, Durlauf et al. (2008) carries out Monte Carlo simulations and shows that this two-stage least square BMA approach (2SLS-BMA) approximates the data generating process accurately.

We use financial reform index by Abiad et al. (2010) and legal origin data from Porta et al. (1999) as the instruments. Financial reform index incorporates information on credit conditions, financial market supervision, or competition characteristics. It represents the reform inputs (initiated typically by international organizations such as International Monetary Fund) and not reform outcomes and therefore, it likely to be independent from growth. At the same time, financial reforms spur financial development (Tressel and Detragiache, 2008). Porta et al. (1998) show how legal origin determines level of investor protection, suggesting common-law origin results is more protective legislation compared to French, German, and Scandinavian civil-law foundation. Legal origin helps explain the differences in financial development (Beck et al., 2003; Levine et al., 2000). Given the data limitations, our sample reduced to 55 countries.

5 Results

This section presents two sets of main results. The first one 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 one investigates the importance of new financial indicators capturing not only depth but also stability and efficiency. We address endogeneity of our financial indicators using 2SLS-BMA approach by Durlauf et al. (2008). Addressing endogeneity is important to generate consistent estimates of the effect of finance on growth. Interestingly, Valickova et al. (2015) show that the studies ignoring the simultaneous nature of finance–growth nexus, typically report greater effect of financial development on economic growth.

5.1 Private credit

Figure 1 illustrates the relationship between private credit and economic growth. Linear and quadratic fit, the latter with 95% confidence intervals, is also included. As a preliminary look at the data, we observe some weak and possibly diminishing relationship between credit and growth.

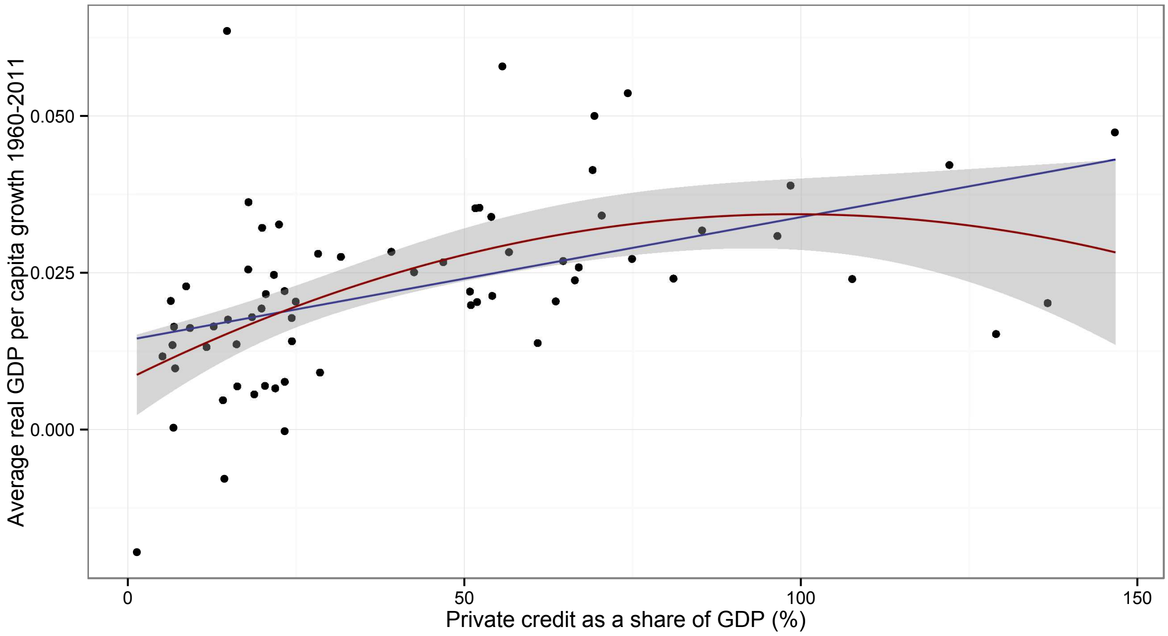

Figure 1: Private credit and growth, 1960-2011

Table 2 presents our baseline results for private credit. We sort the explanatory variables according to their PIPs. We find the initial level of GDP in 1960, dummy variable for Sub-Sahara, share of GDP in mining, fraction of Confucian population, equipment investment, distortions of exchange rate, and covariates capturing the black market characteristics to exhibit the highest PIPs. These findings are broadly in accord with the specification from Fernandez et al. (2001) despite the choice of alternative parameter prior and extended time period under consideration.

Although the private credit ranks almost in the middle of the list of explanatory variables, its PIP is only 7%. This result indicates that credit is very rarely included as the explanatory variable in the 'true' growth model. The mean value of the coefficient is positive. In addition, Figure 2 shows marginal density of the coefficient on private credit. Note that the distribution is based on conditional inclusion of the variable in the model, therefore the conditional mean value in the figure is higher than reported in Table 2, which takes into account models where the private credit variable absented. All in all, 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) using a uniform model prior. However, we depart from the paper in the selection of parameter prior. Instead of using BRIC prior, we decide to utilize hyper-g prior as it is nowadays considered superior in the literature. The essential disadvantage of utilizing BRIC prior is documented by Feldkircher and Zeugner (2012). They describe a phenomenon of 'supermodel effect' arguing that with a high fixed prior

Table 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 labour 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
Nonequipment 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 enrolment	0.05	0.00027	0.00214
Fraction Protestants	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 enrolment	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

g the Shrinkage-factor $\frac{g}{1+g}$ in Equation 14 increases, consequently elevates the size penalty and may skew the posterior model distribution to smaller models. Such choice of large g under fixed priors can result into preference for too simplistic models. According to Feldkircher and Zeugner (2012), the phenomenon is characteristic to BMA applications on growth regressions with numerous covariates. They further claim using model specific hyper-g prior leads to more robust

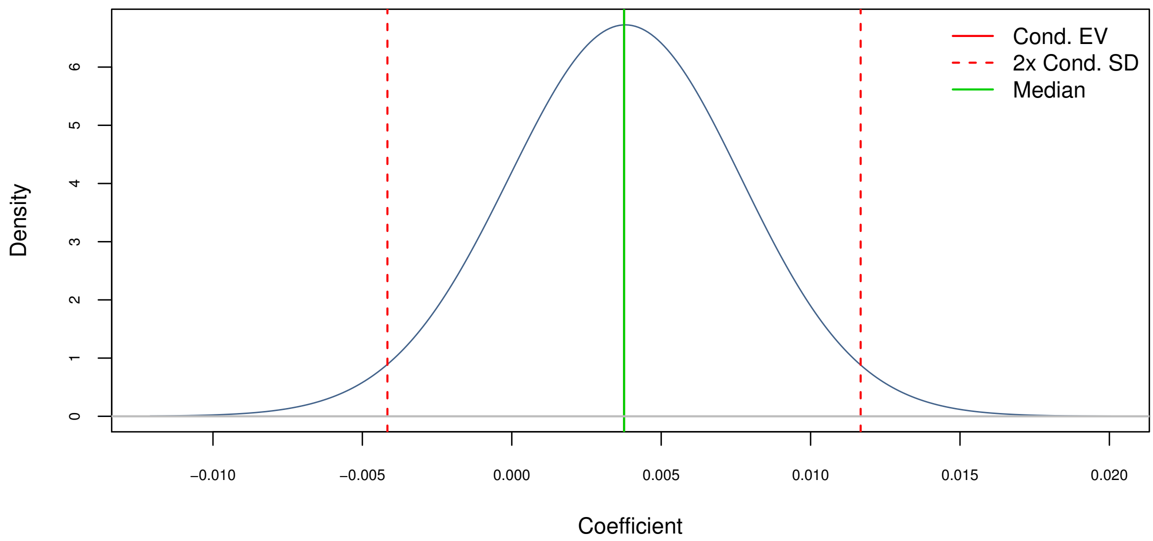

Figure 2: Marginal density, private credit (PIP 7%)

estimates. This is why we abstain from employing BRIC prior and also focus on alternative options for parameter priors in our robustness checks.

Birth-death MC^3 sampler described in Section 4.8 is our primary choice for approximating the PMP distribution. To ensure sufficient convergence of the sampler, we specify 15 000 000 iterations with 3 000 000 initial burn-ins. Table A2 presents the estimation diagnostics. 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 such PMP correlation is far from ideal, but estimation with higher iteration counts and subsequently higher PMP correlation give unvarying results[1]. Note that we below employ different parameter and model prior structure and achieve PMP close to one, 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 the 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 in terms of the MC^3 sampler using 'reverse-jump' algorithm, and model prior, employing random binomial model prior (see Zeugner (2011) for details).

The model comparison is available in Figure 3. Model 1 shows the PIPs under our baseline specification. Model 2 utilizes the same priors, but apply 'reverse-jump' MC^3 algorithm. Model 3 and 4 portray the results when we use UIP under birth-death and reverse-jump sampler respectively. While employing the reverse-jump sampler only marginally alters the PIPs,

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

switching to UIP prior leads to slightly lower inclusion probabilities and model size. Overall, these findings indicate that our baseline results are robust.

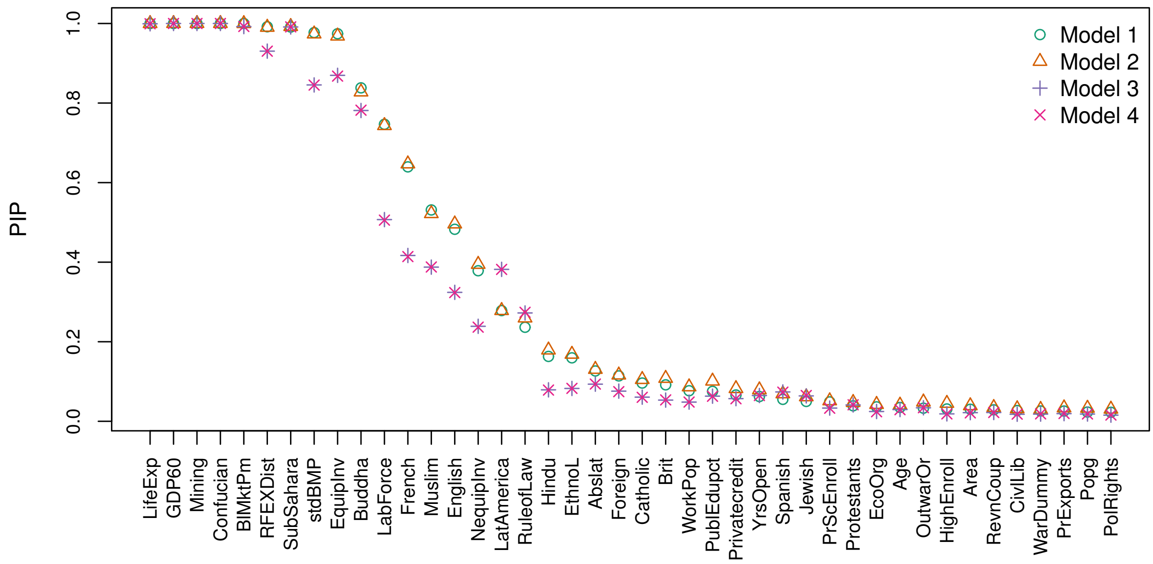

Figure 3: Model comparison with private credit, Model 1=hyper-g,birth-death; Model 2=hyper-g,reverse-jump; Model 3=UIP,birth-death; Model 4=UIP,reverse-jump

Beta-binomial ('random') model prior presents noteworthy insight. This setting allows for model prior setting less tight around the prior expected model size and limits the risk from imposing any particular one (Ley and Steel, 2009). Thus, if the 'true' model size is lower than expected by the prior (21), we should expect the mean model size to shrink in this setting. We present results of the estimation under this model prior in Figure A1. In the first setting with hyper-g prior, mean size shrinks to 15.05 and the PMP correlation between analytical and MC^3 sampler likelihood reaches satisfactory value of 0.96. The most important variables according to their PIPs remain practically the same, although their relative standing adjusts. One significant change is the drop in PIP of volatility of the black market premium to 14%. Lastly, the inclusion probability of private credit increases marginally to 9%.

Finally, we examine the importance of various subsamples as well as the possibility of non-linear relationship between private credit and growth. Several recent studies on financial development and economic growth pay a lot of attention has recently been given to non-linearities of financial development and economic growth (see, for example, Cecchetti and Kharroubi (2012); Law and Singh (2014)). We additionally introduce the squared value of private credit to GDP to examine the diminishing returns of finance on growth. We also limit the time-period under consideration to 1960-1990 and examine whether the effect of financial development turns out stronger for this time period as suggested by Rousseau and Wachtel (2011). We find none of these modifications to severely affect our primary results about the effect of private credit and economic growth. The squared value of private credit comes out with a negative sign, suggesting potential diminishing effect, but with very low PIP. The PIP of private credit estimated on sub-sample before 1990 does not seems to differ from the one on the full time period up to 2011. These results are available upon request.

5.2 New Financial Development Indicators

This section covers additional indicators characterizing varying aspects of financial development and their influence on growth. Namely, we 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 financial sector. Specifically, they propose bank Z-score to be a measure of stability of banking sector, net interest margin to capture the efficiency of banking sector, stock market turnover the efficiency of the stock market, and stock market capitalization to measure its depth. Especially the first two are rarely used in growth regressions (Berger et al. (2004) and Hasan et al. (2009) being the exceptions), even though they might depict the links outlined by the theory in a better way than traditionally applied variables. As we outline in Section 3, the main issue lies in their availability. Although the GFDD provides a significant improvement in this regard, many series are available since the late 1980s. In addition, we keep domestic credit to private sector among the covariates to account for the overall size of the banking sector.

Figure 4 provides a first look on the interaction between individual financial indicators and economic growth. First, we observe a distinct inverse relationship between net interest margin and economic growth. Second, bank Z-score and growth display only marginally positive relationship. Third, market capitalization and market turnover seem to be positively related to growth, which is in line with Levine and Zervos (1998). In addition, Table 3 provides the correlations among the financial indicators. The correlations are typically far from one giving additional impetus to examine more measures of financial development in growth regressions.

Table 3: Correlation matrix of new financial indicators

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

We first provide the results on the first stage regression, where we regress the endogenous financial indicators on instruments. The results are available in Table A4 in the Appendix. We find that the instruments are statistically significant with expected sign. The F-statistic of the regression is 18.3 and adjusted R-squared 0.56.

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

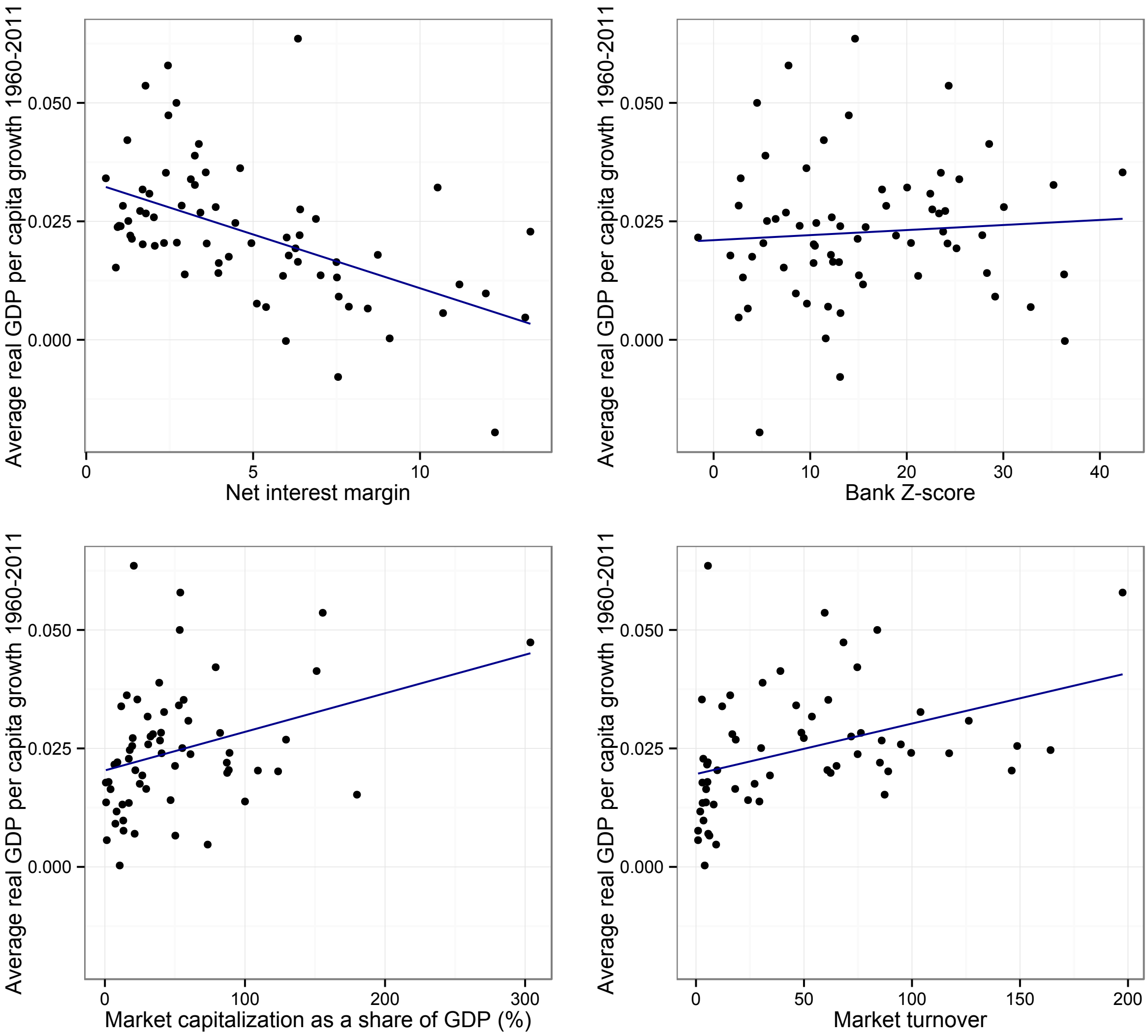

Figure 4: Financial indicators and growth

Table A3 offers the summary of estimation diagnostics. As in the case of previous subsection, running more iterations does not affect the resulting PIPs, although it leads to higher convergence of the sampler. We focus dominantly on the interpretation of results concerning financial indicators as the other explanatory variables' PIPs remain widely similar to specification with private credit.

We present the posterior statistics of explanatory variables in Table 4. Interestingly, the variable proxying for the bank efficiency exhibits comparatively higher PIP to the one reflecting its depth. The net interest margin ranks high among the explanatory variables with 97% inclusion probability. The posterior mean of the coefficient is negative, in accordance with our expectations. The marginal density for the net interest margin is shown in Figure 5. Lower interest margin stems from lower discrepancy between borrowing and lending rates of banks. Thus, if banks are able to channel resources at lower margin, it seems to positively affect long-term economic growth. Effectively similar finding has also been established by Rousseau

Table 4: New financial indicators and growth 1960-2011, baseline results
2SLS–Bayesian model averaging

	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 Protestants	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 labour 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 enrolment	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 enrolment	0.03	-0.00007	0.00129
Ethnolinguistic fractionalization	0.03	-0.00001	0.00064
Market capitalization	**0.02**	**1.1e-07**	**3.3e-06**
Civil liberties	0.02	0.00001	0.00016

(1998) about loan-deposit spread and growth in the United States. Secondly, posterior mean of bank Z-score turns out positive, implying stable banking systems benefit economic growth, though the PIP at 25% does not give much confidence about Z-score to be a crucial growth determinant. Stock market turnover is not given too much importance either, standing third out of the financial indicators with the PIP of 17%. The positive sign of mean is in line with our expectations about the efficient resource allocation being beneficial for growth. Moreover, it supports the conclusions of Levine and Zervos (1998) about active stock market contributing to economic growth. However, we want to point out this indicator might not be capturing the efficiency of the markets coherently. On the one hand, high turnover ratio could reflect low friction to trade and spread of information (Levine, 2005). On the other hand, it may also arise from high amounts of speculative and high-frequency trading activities. Zhang (2010) mentions high-frequency trades in the US represent more than 70% of trading volume. Strikingly, the measures capturing the depth of both banking and stock market sector share negligible inclusion PIPs. Overall, our results show that the measurement of financial development is crucial for the estimated effect of finance on growth.

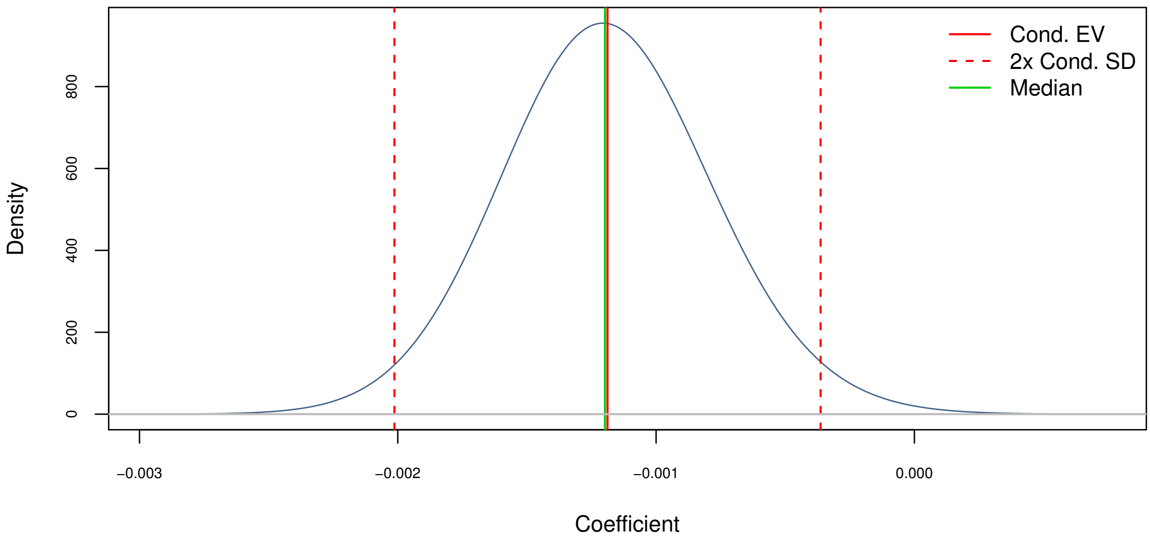

Figure 5: Marginal density, net interest margin (PIP 97%)

While the low PIP of private credit may seem contrary to the established testimony on banking sector size and growth by King and Levine (1993), the finding about growth to be independent to the bare stock market size is consistent with previous literature (Levine and Zervos, 1998; McCaig and Stengos, 2005). To provide some robustness checks, we again carry out the estimation with UIP parameter and random model prior[2]. Figure 6 illustrates the comparison. The implications of different prior are similar to the ones experienced with estimation on private credit. UIP parameter prior subtly alters the PIPs of covariates without major

[2]We also performed estimations using alternative MC^3 sampler, but the differences in posterior statistics were marginal.

impact on interpretation. Giving more leeway to model size by assuming random model prior reduces the posterior mean model size along with PIPs of several variables, but the set of top ranked regressors remains largely invariant. Relative importance of financial indicators changes to some extent. Net interest margin remains among the most important variables with 86% PIP. All of the remaining indicators show low PIPs below 10%. This is due to small lower size induced by random model prior.

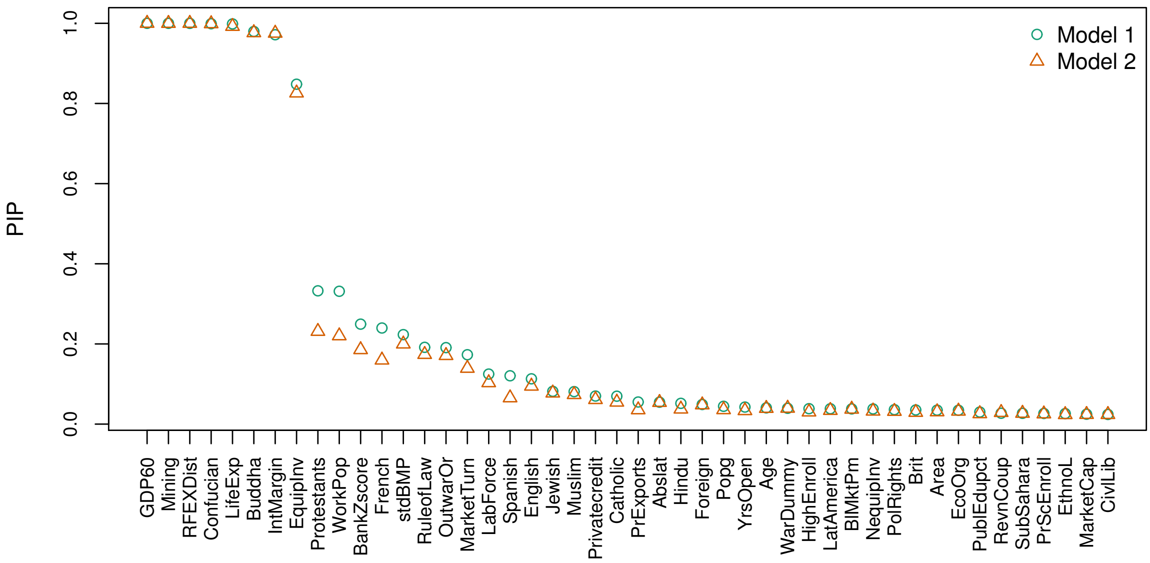

Figure 6: Model comparison with all financial indicators 1960-2011, priors Model 1=hyper-g, Model 2=UIP.

Our baseline estimation suggests that bank efficiency is crucial for growth. We carry out an additional estimation to check the robustness of this finding. Instead of 2SLS–BMA, we estimate BMA with lagged covariates. Given the data availability, we use real growth of GDP per capita in 2000–2011 and we take an average for the 1980s-1990s for the new financial indicators. The advantage of this approach is that we examine how past financial indicator influence current growth. Clearly, the disadvantage is that the time coverage for dependent variable is just a bit more than a decade. We present the results in Table 5. Interestingly, the results remain largely unchanged. The net interest margin remains among the covariates with the highest PIP. The posterior mean of coefficient is negative. The PIP of private credit is 49% but the mean is negative. We hypothesize that the negative mean is a consequence that our sample includes the current global financial crisis characterized by deleveraging in many developed countries. The PIP of other financial indicators is not high.

Table 5: New financial indicators and growth 2000-2011, baseline results Bayesian model averaging

	PIP	Post Mean	Post SD
War dummy	1.00	0.01123	0.00268
Latin America dummy	1.00	0.01651	0.00434
Outward orientation	1.00	0.00899	0.00252
Fraction GDP in mining	1.00	0.08911	0.01722
Fraction Confucian	1.00	0.04158	0.01096
Primary exports	1.00	0.01711	0.00485
Ratio of workers to population	1.00	0.04149	0.00865
Revolutions and coups	1.00	-0.03340	0.00618
Political rights	1.00	0.00640	0.00148
Exchange rate distortions	1.00	0.00022	0.00004
Non-equipment investment	1.00	-0.09586	0.02639
Net interest margin	1.00	-0.00211	0.00053
Sub-Sahara dummy	1.00	-0.03638	0.00857
Fraction Hindu	0.93	0.03717	0.01395
SD of black market premium	0.89	0.00003	0.00001
Private credit	0.49	-0.00003	0.00004
Life expectancy	0.25	0.00009	0.00020
Bank Z-score	0.25	-0.00005	0.00011
High school enrolment	0.15	-0.00689	0.02009
French colony dummy	0.15	-0.00084	0.00293
Degree of capitalism	0.12	0.00012	0.00050
Size of labour force	0.11	0.00000	0.00000
Absolute latitude	0.10	0.00001	0.00004
Black market premium	0.09	0.00065	0.00313
Number of years of open economy	0.08	0.00025	0.00180
Civil liberties	0.08	-0.00016	0.00086
Rule of law	0.08	0.00046	0.00235
Spanish colony dummy	0.06	-0.00026	0.00184
Fraction Catholic	0.06	-0.00011	0.00093
Market turnover	0.06	0.00000	0.00000
Age	0.06	0.00000	0.00001
Market capitalization	0.05	0.00000	0.00000
Fraction Muslim	0.05	0.00018	0.00156
Population growth	0.05	-0.00463	0.04890
Fraction Buddhist	0.04	-0.00012	0.00125
British colony dummy	0.04	0.00002	0.00054
GDP level in 2000	0.04	0.00005	0.00051
Fraction speaking foreign language	0.04	0.00007	0.00070
Primary school enrolment	0.04	0.00021	0.00201
Ethnolinguistic fractionalization	0.04	0.00012	0.00115
Fraction of pop. speaking English	0.04	-0.00008	0.00082
Fraction Protestants	0.04	0.00006	0.00081
Area	0.03	0.00000	0.00000
Public education share	0.03	0.00106	0.01759
Equipment investment	0.02	0.00013	0.00604
Fraction Jewish	0.02	0.00002	0.00099

6 Conclusions

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

Second, previous literature examining finance-growth nexus largely employs the measures of financial depth (both for banking sector and stock markets) but rarely examines the measure of 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 the depth but also efficiency and stability. It is vital to revisit finance and growth literature also because the recent studies questions the contribution of finance to growth and argues that too much finance harms growth (Cecchetti and Kharroubi, 2012; Law and Singh, 2014).

Using the updated well-known cross-country growth dataset by Fernandez et al. (2001), we find that the traditional indicators of financial depth (as well its squared terms) are not robustly related to long-term economic growth. The measures of financial depth as well as financial stability exhibit posterior inclusion probability well below 50%. On the other hand, our results suggest that bank efficiency, as proxied by net interest margin, is crucial for growth. The corresponding posterior inclusion probability is on average above 90%. This result is in line with theory that financial sector is crucial in channeling resources from savers to borrowers. These results are robust to different parameter and model priors in Bayesian model averaging. The results are also robust once we address endogeneity of financial indicators.

Overall, we find that the measurement of financial development is crucial for the estimated effect of finance on growth. Our results attribute greater role to the banking sector and its efficiency in fostering economic growth. In terms of policy implications, our results indicate that the current wave of regulatory changes to safeguard financial stability should carefully analyze the consequences for the efficiency of financial intermediaries.

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A1 Description of the Dataset

We use commonly employed the dataset on the growth determinants and by Fernandez et al. (2001). The dataset contains 41 explanatory variables potentially important for growth on 72 countries. We describe the variables, which do not assess the 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 PWT, extending considered time period from former 1960-1992 to 1960-2011. Our dependent variable is average growth of real output-based GDP per capita. The mean value of growth rate across the dataset is 2.27% with standard deviation of 1.45%. The regressors in the dataset comprise of various measures of economical, political, geographical, demographic, social, and cultural factors. As a great number of variables is of endogenous nature with respect to growth, the data typically comes from 1960 or before.

Economic variables mostly cover established factors from neoclassical growth theories. The initial level of GDP is present to capture conditional convergence, such that lower starting levels imply higher growth rates (Barro and Sala-i-Martin, 1992). Additionally, investment into physical capital 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 enrolment, higher education enrolment and public education share from Barro (1996). Life expectancy is often assumed to capture human capital other than education, therefore it is also present among the regressors. Exchange rate fluctuations, black market premium, and volatility of black market premium account for degree of economic uncertainty. Exchange rates can affect foreign direct investments and net export of the country, subsequently influencing economic growth. Black market premium then shows the surplus on exchange rate over the official foreign exchange market. High discrepancy mirrors higher uncertainty and along with high volatility we expect it to decelerate growth. Moreover, set of variables accounts for economic policies. Outward orientation based on import-export structure reflects possible impact of international competition on domestic production efficiency. Economic organization captures the degree of capitalism, using the classification by Hall and Jones (1996). The characteristic is measured on six degree scale from 'statist' to 'capitalist' dependent on how much control over the economy national government exerts. Lastly, degree of openness enters through the length of period the country has experienced open economy. All policy variables are assumed to be positively correlated with economic growth.

Geographical controls include dummy variables for Sub Sahara, Latin America, total area, and absolute latitude. Spatial differences in economic growth have been established by the literature. Location of a country may influence growth through differences in transportation costs, disease burdens, or agricultural productivity (Gallup et al., 1999). Location further away from the equator should have positive impact on growth.

Explanatory variables measuring political conditions within countries are colonial heritage, rule of law, indices for political rights, civil rights, and also revolutions and coups. Political instability is further portrayed by war dummy, taking value of one if the country suffered from war between 1960-1992. Acemoglu et al. (2001) note 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 and Tiede, 2011). Civil and political rights further account for level of democracy and its relation to income redistribution. If large portion of income is in the hands of few, it may have consequences on production incentives of economic agents. Intuitively, wars and coups impact growth negatively by decreasing stability and infrastructure destruction.

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 has been previously found relevant to economic growth in Barro (1996). Population growth accounts for neoclassical implication of ceteris paribus decreasing per capita growth with increasing population. Language skills are approximated by the fraction of people speaking English within a country and fraction of people speaking foreign language. Hall and Jones (1996) demonstrate how better language skills positively reflect in economic growth. They argue it arises from easier internalization of globalization benefits. The full list of variables names and their abbreviations is available below.

Additionally, PWT is missing observations on Algeria, Haiti, and Nicaragua, therefore we have to drop them from the sample. Furthermore, GFDD does not include data for Taiwan. In the end, 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 (Kinhasa), 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, Zimbabwe.

Table A1: List of used variables

Short name	Full name
Abslat	Absolute latitude
Age	Age
Area	Area
BlMktPm	Black market premium
Brit	British colony dummy
Buddha	Fraction Buddhist
Catholic	Fraction Catholic
CivlLib	Civil liberties
Confucian	Fraction Confucian
EcoOrg	Degree of capitalism
English	Fraction of pop. speaking English
EquipInv	Equipment investment
EthnoL	Ethnolinguistic fractionalization
Foreign	Fraction speaking foreign language
French	French colony dummy
GDP60	GDP level in 1960
HighEnroll	High school enrolment
Hindu	Fraction Hindu
Jewish	Fraction Jewish
LabForce	Size of labour force
LatAmerica	Latin America dummy
LifeExp	Life expectancy
Mining	Fraction GDP in mining
Muslim	Fraction Muslim
NequipInv	Non-equipment investment
OutwarOr	Outward orientation
PolRights	Political rights
Popg	Population growth
PrExports	Primary exports
Privatecredit	Private credit
Protestants	Fraction Protestants
PrScEnroll	Primary school enrolment
PublEdupct	Public education share
RevnCoup	Revolutions and coups
RFEXDist	Exchange rate distortions
RuleofLaw	Rule of law
Spanish	Spanish colony dummy
stdBMP	SD of black market premium
SubSahara	Sub-Sahara dummy
WarDummy	War dummy
WorkPop	Ratio of workers to population
YrsOpen	Number of years of open economy
BankZscore	Bank Z-score
IntMargin	Net interest margin
MarketCap	Stock market capitalization to GDP
MarketTurn	Stock market turnover ratio
Privatecredit	Domestic credit to private sector

Table A2: Model diagnostics, private credit baseline estimation

Mean # regressors	**Draws**	**Burnins**	**# models visited**
19.09	1.5e+07	3e+06	9224946
Modelspace 2^K	**% visited**	**% Top models**	**Corr PMP**
4.4e+12	0.00021	0.3	0.5672
# obs	**Model prior**	**g-prior**	**Shrinkage-Stats**
68	uniform/21	hyper (a=2.029)	Av=0.909

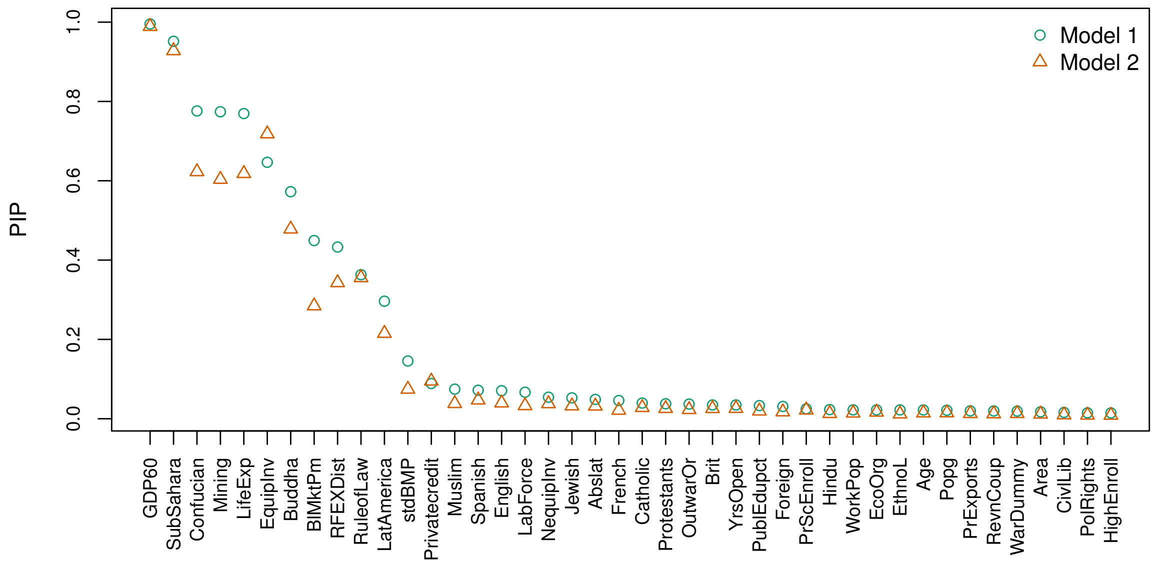

Figure A1: Model comparison with private credit, Model 1=hyper-g, random model prior; Model 2=UIP, random model prior

Table A3: Model diagnostics, financial indicators baseline regression

Mean # regressors	**Draws**	**Burnins**	**# models visited**
19.28	3e+06	1e+06	2139349
Modelspace 2^K	**% visited**	**% Top models**	**Corr PMP**
7e+13	3e-06	0.55	0.1316
# obs	**Model prior**	**g-prior**	**Shrinkage-Stats**
60	uniform/23	hyper (a=2.033)	Av=0.907

Table A4: First stage regression results, 2SLS BMA

	PC1
Financial reform index	-5.700^{***}
	(0.815)
Reference: Legal origin French	
Legal origin UK	-0.341
	(0.321)
Legal origin German	-1.370^{**}
	(0.546)
Legal origin Scandinavian	-0.388
	(0.598)
constant	3.267^{***}
	(0.448)
Observations	55
R^2	0.594
Adjusted R^2	0.562
F Statistic	18.296^{***} (df = 4; 50)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table A5: First stage regression results, 2SLS BMA, Net interest margin

	Net interest margin
Financial reform index	-8.992^{***}
	(1.803)
Reference: Legal origin French	
Legal origin UK	0.765
	(0.710)
Legal origin German	-1.547
	(1.208)
Legal origin Scandinavian	-1.544
	(1.322)
constant	8.978^{***}
	(0.991)
Observations	55
R^2	0.451
Adjusted R^2	0.407
F Statistic	10.257^{***} (df = 4; 50)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table A6: First stage regression results, 2SLS BMA, Bank Z-score

	Bank Z-score
Financial reform index	−0.248
	(7.118)
Reference: Legal origin French	
Legal origin UK	−1.057
	(2.803)
Legal origin German	−2.146
	(4.769)
Legal origin scandinavian	3.904
	(5.222)
constant	15.015***
	(3.914)
Observations	55
R^2	0.022
Adjusted R^2	−0.056
F Statistic	0.286 (df = 4; 50)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table A7: First stage regression results, 2SLS BMA, Market capitalization

	Market capitalization
Financial reform index	186.359***
	(30.447)
Reference: Legal origin French	
Legal origin UK	32.686***
	(11.989)
Legal origin German	6.510
	(20.398)
Legal origin scandinavian	−4.550
	(22.337)
constant	−55.969***
	(16.742)
Observations	55
R^2	0.496
Adjusted R^2	0.456
F Statistic	12.307*** (df = 4; 50)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table A8: First stage regression results, 2SLS BMA, Market turnover

	Market turnover
Financial reform index	66.270**
	(32.453)
Reference: Legal origin French	
Legal origin UK	13.065
	(12.779)
Legal origin German	56.129**
	(21.742)
Legal origin scandinavian	28.554
	(23.808)
constant	5.066
	(17.845)
Observations	55
R^2	0.248
Adjusted R^2	0.188
F Statistic	4.122*** (df = 4; 50)
Note:	*p<0.1; **p<0.05; ***p<0.01