Does Trust Promote Growth?

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Abstract

We examine the effect of interpersonal trust on long-term economic growth. Unlike previous studies in this stream of literature, we use the Bayesian model averaging to deal rigorously with model uncertainty. Examining more than forty regressors for nearly fifty countries, our estimates show that trust exerts a positive effect on long-term growth and suggest that trust is one of key drivers of long-term growth. In addition, our results do not support the view that the relationship between trust and growth is non-linear and that a high level of trust is be detrimental for growth.

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Keywords: trust, economic growth, Bayesian model averaging.

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1 Introduction

The importance of trust has been recognized for a long time in economic literature. Many scholars with a major impact on economic profession highlighted the role of trust for economic development (Smith (1997 [1766]) or Keynes (1936), among others). This long-term interest of economists in trust sharply contrasts with the shortage of empirical studies assessing robustly the effect of trust on growth.

The handful econometric evidence typically puts forward that trust is a vital determinant of economic growth. Knack and Keefer (1997) and Zack and Knack (2001) pioneer this stream of literature using the data on interpersonal trust obtained from World Values Survey database. Controlling for several standard determinants of growth, they document that trust is positively associated with growth.

Closely related literature examines the importance of trust in large organizations (La Porta et al. (1997)), measuring trust using experiments (Glaeser et al., 2000) or the determinants of trust (Alesina and La Ferrara, 2002, or Bjornskov, 2006). Aghion et al. (2010) investigate the effect of distrust on government regulation arguing that regulation serves as the substitute for trust. Algan and Cahuc (2010) highlight the importance of inherited trust for economic growth in the 20th century. Tabellini (2005) shows how culture, which is measured as the set of indicators including the trust, has significantly affected the economic development in Europe. Using the data on trust in U.S. regions, Dincer and Uslaner (2010) widens the scope of possible impact of trust and show that trust positively contributes not only on economic growth, but also on the growth rate of housing prices and the growth rate of employment.

Most of above mentioned contributions concentrate on evaluating the casual effect of trust on growth. However, they focus less on model uncertainty, which has been emphasized as highly important issue in empirical growth literature (Fernandez et al. (2001a), Sala-i-Martin et al. (2004), Ley and

Steel (2009), Eicher et al. (2011)). The potentially plentiful determinants of growth with many competing growth theories naturally give rise to large uncertainty about which model represents the "correct" model of economic growth (Durlauf et al., 2008).[1] Beugelsdijk et al. (2004) and Berggren et al. (2008) examine the effect of trust on growth using the original dataset of Zack and Knack (2001) and include some more recent observations and more countries. To assess the robustness of trust-growth nexus, Beugelsdijk et al. (2004) and Berggren et al. (2008) employ extreme bounds analysis, and least trimmed squares in the case of latter article. The results suggest that the effect of trust on growth is not robust. We contribute to this literature and examine whether the pessimistic view about the importance of social capital indeed holds. For this reason, we deal rigorously with model uncertainty within formal probabilistic reasoning – using Bayesian model averaging (BMA). Unlike extreme bounds analysis[2], BMA is well grounded in statistical theory (Raftery, 1995, Raftery et al., 1997). Model uncertainty is a part of estimation procedure and the assumption that all specifications are equally likely to be true is relaxed.

Our results suggest that the interpersonal trust is a robust determinant of long-term economic growth. Examining more than forty regressors for nearly fifty countries around the world, our estimates show that trust is one of key drivers of long-term economic development. Our BMA estimation shows that trust exhibits a high posterior inclusion probability (typically around 0.8), which suggests that trust is likely to belong in the "correct" model of economic growth. Therefore, our results do not support the previous findings claiming that the effect of trust on growth is sensitive to the conditioning set of regressors. In addition, in contrast to previous evidence our results also do not give support to the finding that a high level of trust is detrimental for

[1] Model uncertainty has been recognized as important issue in political science literature, too. See Montgomery and Nyhan (2010) for a recent discussion.

[2] Leamer (1978) develops extreme bounds analysis as an *ad hoc* sensitivity analysis to address model uncertainty.

growth. For this reason, we include the squared trust among the potential determinants of growth and find that the squared trust is either positive or insignificant, but never negative.

The paper is organized as follows. Section 2 briefly introduces the Bayesian model averaging. Section 3 presents the data. The results are available in section 4. Conclusions are provided in section 5.

2 Bayesian Model Averaging

Following its development in statistics primarily in the 1980s, BMA has gained popularity in economic literature in the 1990s and 2000s. It is typically applied to assess transparently and rigorously the robustness of results especially in the environment of many competing theories and many possible determinants. In a similar vein, BMA techniques are often applied for forecasting in a data rich environment. The textbook treatment of BMA is available in Koop (2003) and Koop et al. (2007). Feldkircher and Zeugner (2009), Ley and Steel (2009) or Eicher et al. (2011) discuss BMA in relation to the determinants of long-term growth. BMA was introduced to political science by Bartels (1997), but somewhat surprisingly was not followed by many other applications. For this reason, Montgemery and Nyhan (2010) provide an extensive discussion of BMA with the emphasis how BMA can be useful in political science.

We continue with a brief formal description of BMA. Suppose we have a dependent variable Y (for example, GDP growth) with a number of observations n (the number of countries in case of cross-sectional growth regressions) and k regressors $X_1.....X_k$. The researcher is interested to understand, which regressors $X_1.....X_k$ are robust determinants of Y. The researcher typically specifies some core model with a subset of regressors $X_1.....X_k$ and then includes additional regressors within the set of $X_1.....X_k$ to assess the robustness of core model results. In many applications, this is done in somewhat idiosyncratic and non-transparent manner. This procedure is also vulnerable to inflating the true significance of regression coefficients. Clearly, the risk of omitting some important regressor is far from negligible. The BMA offers an alternative to this model search procedure, and as the name suggests it focuses on model averaging rather than on model selection.

The standard procedure in a cross-sectional growth determinants literature is to estimate model $Y = \alpha_1 X_1 + .. + \alpha_k X_k + e$, where $e \sim N(0, \sigma^2 I)$ (assume for simplicity that X_1 is a constant) using OLS. Typically, there is a substantial uncertainty, which of possibly plentiful X's should be included. In consequence, there are $l = 2^k$ subsets of X's that can be considered as regressors and therefore $M_1 .... M_l$ regression models to be examined. Let us denote the vector of parameters of i-th model as $\theta_i = (\alpha, \sigma)$ .The likelihood function of i-th model, $pr\,(D \mid \theta_i, M_i)$, summarizes all the information about θ_i based on available data D. The marginal likelihood, the probability density of the data, D, conditional on M_i can be written as follows

$$pr\,(D \mid M_i) = \int pr\,(D \mid \theta_i, M_i)\, pr\,(\theta_i \mid M_i)\, d\theta_i, \tag{1}$$

the marginal likelihood is therefore a product of the likelihood function $pr\,(D \mid \theta_i, M_i)$ and prior density $pr\,(\theta_i \mid M_i)$ integrated over the parameter space. Using $pr\,(D \mid M_i)$ one can derive the prior probability that M_i is a correct model, which we denote as $pr\,(M_i)$. Bayes's theorem gives the posterior model probability of M_i, $pr\,(M_i \mid D)$,

$$pr\,(M_i \mid D) = \frac{pr\,(D \mid \theta_i, M_i)\, pr\,(M_i)}{\sum_{l=1}^{i} pr\,(D \mid M_l)\, pr\,(M_l)} \tag{2}$$

the posterior inclusion probability of given regressor, $pr\,(\alpha_j \neq 0 \mid D)$, is then received by taking a sum of posterior model probabilities across those models that include the regressor. Posterior inclusion probability is of primary importance here, since it measures the probability that given regressor belongs to the "correct" model. This approach has been recently generalized to panel data setting to explicitly account for unobserved heterogeneity among countries (Benito, 2011).

Even with modern computers, it is computationally prohibitive to evaluate all the possible models and we use MC^3 algorithm to reduce the computational requirements (Madigan and York, 1995). MC^3 approximates the posterior distribution of model space by simulating a sample from it. We take 1 000 000 burn-ins and 3 000 000 draws, which leads to a sufficiently high correlation between analytical and MC^3 posterior model probabilities (about 0.99 in our case).

The parameter priors have to be specified in order to implement BMA. In general, priors specify researcher's information or beliefs before seeing the actual data. Since the degree of belief is not particularly high in the growth regressions context, uninformative priors are typically employed. The priors affect the marginal likelihood in (1). For this reason, Eicher et al. (2011) and Ley and Steel (2009) analyze, which parameter priors (as well as model priors, more on these priors below) are preferable. This is evaluated by comparing the predictive accuracy of identical regression models, which differ only in terms of priors. Eicher et al. (2011) find that among 12 candidate parameter priors the Unit Information Prior (UIP) with uniform model prior tend to provide more accurate forecasts than the other considered priors. On the other hand, the results by Feldkircher and Zeugner (2009) give more support to hyper g-priors. To deal with the issue, we carry out the estimations using several parameter priors to shed further light on the robustness of results.

The first prior is defined as follows.

$$pr\left(D \mid M_i\right) \approx c - 1/2BIC_i, \tag{3}$$

where

$$BIC_i = n \log \left(1 - R_i^2\right) + p_i \log (n) \tag{4}$$

In (3) and (4), c is a constant, R_i^2 stands the coefficient of determination and p_i for the number of regressors. This prior is typically labelled as UIP. Next, we consider the following prior, so-called g-prior, proposed by Fernandez et al. (2001b):

$$pr(\alpha_1 \mid M_i) \propto 1, \tag{5}$$

$$pr(\sigma \mid M_i) \propto 1, \tag{6}$$

$$pr\left(\alpha^{(k)} \mid \sigma, M_i\right) \sim N\left(0, \left(g_k Z^{(k)\prime} Z^{(k)}\right)^{-1}\right), \tag{7}$$

where $Z^{(k)}$ denote the matrix of size $n \times p_k$ with p_k demeaned regressors included in M_i. It is noteworthy that the values of g close to zero imply less informative prior and $g = 1$ gives the same weight to the information contained in data and in prior. Two different values of g are examined. First, $g = 1/\max(N, k^2)$ is the one preferred by Fernandez et al. (2001b) and is called BRIC. Second, $g = 1/(\ln N)^3$ corresponds to Hannah-Quinn criterion. The third commonly employed g-prior set $g = 1/k^2$ (Foster and George, 1984), but this is in our setting identical to $g = 1/\max(N, k^2)$.

Next, we also use parameter priors not employed previously in the growth literature (except Feldkircher and Zeugner, 2009), the so-called hyper-g prior (Liang et al, 2008).

$$\pi(g) = \frac{a}{a-2}(1+g)^{a/2}, \tag{8}$$

We use two different hyper-g priors. The first one sets the prior expected value of shrinkage factor to correspond to UIP, the second one sets it to conform to BRIC. All in all, this makes five different parameter priors that we employ for the empirical investigation of the effect of interpersonal trust on long-term economic growth.

As for the model prior, we use a uniform model prior, which gives equal prior probability to all models M_i. In consequence, $pr(M_i) = 1/L$ for each i. We choose this model prior, because Eicher et al. (2011) show that it performs well in forecasting exercise.

3 Data

To analyze the cross-sectional growth determinants, the widely used Fernandez et al. (2001a) dataset is employed. The original dataset contains 41 regressors from 72 countries leading to a total of 2^{42} models (e.g. more than 2 trillion). The measure of interpersonal or generalized trust, which is obtained from the World Values Survey[3], is available for 46 out of these 72 countries. The World Values Survey is conducted in dozens of countries with typically more than 1000 respondents in each country giving their answer to various questions related to their values. The survey also includes a question on the degree of trust; respondents are asked whether they agree that 'most people can be trusted'. The additional change to this dataset is that we use the long-term growth between 1960-2005. The dataset is largely representative, as there are both developed and developing countries. In addition, it is noteworthy that various economic, political, geographical, demographic social or cultural variables are considered as the potential determinant of growth.

More specifically, the list of regressors is as follows: GDP level in 1960, Fraction Confucian, Life Expectancy, Equipment investment, Sub-Saharan dummy, Fraction GDP in mining, Fraction Hindu, Non-equipment investment, Rule of law, Degree of capitalism, Size labor force, Fraction Mus-

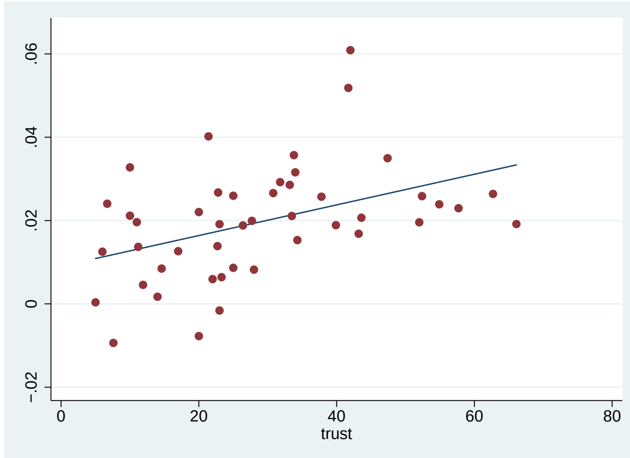
[3] These data are kindly provided by Berggren et al. (2008) at the authors' website.

lim, Fraction Protestants, Black market premium, Latin American dummy, Higher school enrollment, Ethnolinguistic fractionalization, Primary school enrollment, Civil liberties, Fraction Buddhist, Spanish colony dummy, Number of years open economy, Fraction of population speaking English, French colony dummy, Outward orientation, Political rights, Age, War dummy, British colony dummy, Fraction Catholic, Public education share, Primary exports, Exchange rate distortions, Fraction speaking foreign language, Absolute latitude, Population growth, Area, (scale effect), Ratio workers to population, SD of black market premium, Fraction Jewish, Revolutions and coups. Some regressors such as the Sub-Saharan dummy are exogenous to economic growth by construction. Other regressors are contructed in the way to minimize potential endogeneity issues, i.e. the data comes typically from 1950s or 1960s. The further details about the dataset are available in Fernandez et al. (2001a).

These regressors are available for the following countries: Algeria, Argentina, Australia, Austria, Belgium, Bolivia, Botswana, Brazil, Cameroon, Canada, Chile, Colombia, Congo, Costa Rica, Cyprus, Denmark, Dominican Rep., Ecuador, El Salvador, Ethiopia, Finland, France, Germany West, Ghana, Greece, Guatemala, Haiti, Honduras, Hong Kong, India, Ireland, Israel, Italy, Jamaica, Japan, Jordan, Kenya, Korea, Madagascar, Malawi, Malaysia, Mexico, Morocco, Netherlands, Nicaragua, Nigeria, Norway, Pakistan, Panama, Paraguay, Peru, Philippines, Portugal, Senegal, Singapore, Spain, Sri Lanka, Sweden, Switzerland, Taiwan, Tanzania, Thailand, Tunisia, Turkey, Uganda, United Kingdom, United States, Uruguay, Venezuela, Zaire, Zambia, Zimbabwe.

The alternative is to use the dataset from Berggren et al. (2008). The original dataset contains 24 regressors from 64 countries. Nevertheless, there are missing observations for various countries and this consequently decreases the number of countries for the BMA to 45. The cross-country coverage of this dataset is thus similar to the modified dataset of Fernandez et al.

Figure 1: Trust and growth, cross-country evidence



(2001a), but the number of possible determinants of growth is lower. Therefore, the Fernandez et al. (2001a) dataset is employed.

4 Results

Figure 1 presents the scatter plot between interpersonal trust and growth and clearly documents that there is a positive relationship between these two variables. This is reconfirmed by a simple correlation coefficient with the value of 0.43. The value is different from zero at 1% significance level.

Table 1 presents the baseline results on the determinants of long-term growth. For the baseline case, we choose the UIP prior with uniform model prior. The choice of this prior structure is motivated by the recent findings of Eicher et al. (2011), who evaluate a variety of candidate priors and find that the UIP prior with uniform model prior generally performs the best in terms of predictive performance. It is worth mentioning that the evaluation of predictive performance is carried out using the dataset almost identical to ours. Table 1 shows the posterior inclusion probability (i.e. probability that given regressor is included in the "correct" or "ideal" model, abbreviated as

PIP), posterior mean and posterior standard deviation for all 42 regressors. The variables are ranked according to their PIP.

The results indicate that trust is a vital determinant of long-term economic growth. As expected, the posterior mean is positive. This suggests that the long-term economic growth is higher in countries with greater interpersonal trust. This is in line with previous evidence emphasizing that trust improves the smooth functioning of business, or more generally reduces transaction costs in a society, and ultimately contributes to growth (Whiteley (2000), Keefer and Zack (2001) or Dincer and Uslaner (2010)). On the other hand, the results show that the effect of trust on growth is more robust than previously thought (see Beugelsdijk et al. (2004) and Berggren et al. (2008)). In general, our findings for other regressors are broadly in line with previous evidence on the cross-sectional growth determinants the within BMA framework (Fernandez et al. (2001a)).

Table 2 focuses on the sensitivity to selected prior structures and reports the results on the effect of trust and of squared trust on growth. For simplicity, the PIP, posterior mean and posterior standard deviation for all other 41 regressors is not reported, but available upon request. Eicher et al. (2011) find that the PIPs for some growth determinants, to a certain extent, varies depending on the prior structure. We find that the PIP is around 0.8 for fixed-g priors and somewhat lower for hyper-g priors. The posterior mean remains positive.

In addition, we also assess whether the squared trust determines growth. Using several cross-sectional and panel data models, Roth (2009) finds the curvilinear relationship between trust and growth suggesting that too much trust harm growth (the squared trust is found to have a negative effect on growth). We subject this finding to a robustness check within our econometric framework. However, our results do not give support to the finding that a high level of trust is detrimental for growth. To the contrary, as reported in Table 2, we find that the squared trust exerts a positive effect on

Table 1: The determinants of growth, baseline results

Variable	PIP	Post Mean	Post SD
GDP level in 1960	1	-0.015066	0.002473
War dummy	0.97	-0.008385	0.002699
Fraction Confucian	0.97	0.089060	0.026909
SD of black market premium	0.96	-4.94E-05	1.62E-05
Fraction Hindu	0.95	-0.091265	0.030508
Population growth	0.95	-0.589666	0.212866
Fraction GDP in mining	0.94	0.105029	0.039356
Size labor force	0.94	3.24E-07	1.16E-07
Fraction Jewish	0.90	-0.526445	0.245591
Degree of capitalism	0.89	0.002593	0.001290
Fraction Protestants	0.86	-0.010658	0.005917
Outward orientation	0.82	0.003396	0.002174
Trust	0.81	0.000179	0.000117
Life Expectancy	0.69	0.000387	0.000344
Public education share	0.57	0.097867	0.109924
Number of years open economy	0.42	0.002494	0.003841
Primary school enrollment	0.38	0.004341	0.008086
Rule of law	0.35	0.003299	0.006148
Political rights	0.29	-0.000300	0.000736
Equipment investment	0.28	0.016934	0.039397
Sub-Saharan dummy	0.28	-0.001173	0.004685
Age	0.28	-6.80E-06	1.49E-05
Higher school enrollment	0.27	-0.008393	0.023815
Civil liberties	0.27	-0.000251	0.000791
Ratio workers to population	0.25	-0.000378	0.007735
Fraction Muslim	0.24	0.001189	0.004948
Fraction Catholic	0.23	0.000778	0.003581
French colony dummy	0.22	0.000735	0.002209
Fraction Buddhist	0.21	0.001735	0.005875
Primary exports	0.20	-0.001206	0.004988
Latin American dummy	0.19	-0.000191	0.001881
Ethnolinguistic fractionalization	0.19	0.000463	0.002003
Revolutions and coups	0.18	-0.000239	0.002032
British colony dummy	0.18	0.000252	0.001406
Non-equipment investment	0.17	0.002077	0.010338
Spanish colony dummy	0.16	-2.44E-05	0.001426
Area (scale effect)	0.16	3.15E-08	1.72E-07
Black market premium	0.16	0.000174	0.002170
Exchange rate distortions	0.16	-1.26E-06	1.62E-05
Absolute latitude	0.16	-1.49E-06	5.42E-05
Fraction of pop. speaking English	0.15	0.000131	0.001404
Fraction speaking foreign language	0.15	7.90E-05	0.001032

growth albeit the posterior standard deviations are typically large. The PIP of squared trust is around 0.3 and the PIP of trust somewhat decreases to 0.7 using our baseline specification of prior structure.

Zack and Keefer (2001) or Roth (2009) discuss the potential endogeneity arising due to data availability of trust. The World Values Survey reports the first cross-country measures of trust at the beginning of 1980s, but for many countries these data are not available sooner than in the 1990s. However, Zack and Keefer (2001) or Roth (2009), among others, argue that the endogeneity bias is likely to be small. This is because the trust is unlikely to change rapidly over time. Indeed, the correlations of trust between various waves of World Values Survey are higher than 0.9.

5 Concluding Remarks

We examine the effect of interpersonal trust on long-term economic growth. Numerous anecdotal evidence as well as growing empirical literature typically put forward that trust is positively related to growth (see Aghion et al. (2010), Algan and Cahuc (2010) or Zack and Keefer (2001), among others). Nevertheless, existing evidence also put forward that the effect of trust on growth is far from robust (Beugelsdijk et al. (2004) and Berggren et al. (2008)). Therefore, we focus on the robustness of relationship between trust and growth and assess the role of model uncertainty in a full manner.

The typical article within this stream of literature regressed trust on growth and varied the conditioning set of variables to get a feeling of the robustness of the results. It has been shown that this strategy is more likely to lead in significant results (Raftery et al., 1997). In addition, the choice of conditioning set of regressors is somewhat *ad hod*, especially for growth literature with dozens of possible determinants of growth (and thus with a high degree of model uncertainty). Sala-i-Martin et al. (2004) or Fernandez et al. (2001) examine about forty different growth determinants within

Table 2: The effect of trust on growth, various prior structures

	(1)	(2)	(3)	(4)	(5)	(6)
Trust						
Post. Incl. Prob.	0.81	0.71	0.84	0.74	0.64	0.62
Posterior mean	0.018	0.017	0.019	0.019	0.017	0.014
Posterior SD	0.009	0.015	0.009	0.015	0.009	0.017
Squared trust						
Post. Incl. Prob.	—	0.29	—	0.29	—	0.30
Posterior mean	—	0.041	—	0.007	—	0.091
Posterior SD	—	0.019	—	0.187	—	0.201
Parameter prior	g	g	g	g	hyper-g	hyper-g
Par. prior value	UIP	UIP	Hannah	Hannah	BRIC	BRIC
Model prior	Uniform	Uniform	Uniform	Uniform	Uniform	Uniform

Notes: The posterior mean and standard deviation on trust and squared trust multiplied by 100 and 1,000,000, respectively. For the sake of brevity, the results for other 41 regressors not reported.

unified framework suitable to deal with model uncertainty – Bayesian model averaging. However, any of previous studies does not examine the role of interpersonal trust within this framework. We bridge this gap and investigate whether trust is a robust determinant of growth using the dataset very similar to widely used dataset of Fernandez et al. (2001) and Sala-i-Martin et al. (2004).

Our results show that trust is indeed a vital determinant of long-term growth and the countries with higher level of interpersonal trust grow more. Our Bayesian model averaging estimates show a very high post inclusion probability (around 0.8) for trust. This suggests that trust belongs among top determinants of long-term economic growth and in general, gives support to the literature emphasizing the importance of social capital for growth (Tabellini, 2010). This finding is also robust to using various parameter priors. In addition, we also assess, whether there is a non-linear effect of trust on growth adding the squared trust into the data matrix. Unlike the previous literature that found the coefficient on squared trust to be negative, we do find any evidence for a non-linear relationship between trust and economic growth.

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