Stars, Wars, and Development

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Abstract

As part of the credibility revolution in applied economics, researchers need to turn away from significance thresholds and stars, and instead focus on importance. Yet, existing measures of importance in regression analysis have fundamental flaws. Using an axiomatic approach, I develop two measures, which decompose the variance of the dependent variable into contributions associated with each regressor. I demonstrate the relevance and complementarity of the two measures in two cases studies. The first shows that the statistically significant relationship between genetic distance and inter-state wars is economically irrelevant. The second identifies the most important factors of long-term development.

Keywords: Importance, Statistical Significance, Wars, Genetic distance, Long-run growth
JEL Classification: B4, C18, O4

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1 Introduction

Most applied economists, including myself, get very excited when their coefficient of interest turns out to be statistically significant. Most of the time, we proudly showcase our achievement by decorating regression results with one, two, or three significance stars. Statistically significant results are indeed more likely to be published (Andrews and Kasy 2019; Mervis 2014; Doucouliagos 2005), while null-results are often not written up and rarely published (Abadie 2018; Franco et al. 2014). Pressure to publish and publication bias are so strong that many researchers end-up 'p-hacking' their otherwise statistically insignificant results (Brodeur et al. 2016). Condemning these practices, the American Statistical Association (ASA) released a statement on *Statistical Significance and P-Values* in March 2016, emphasizing that *"a p-value, or statistical significance, does not measure the size of an effect or the importance of a result."*. Following this statement, hundreds of scientists have joined a call *"for the entire concept of statistical significance to be abandoned"* (Amrhein et al. 2019). Instead, researchers should embrace uncertainty and carefully examine the importance of findings (Amrhein et al. 2019; Ziliak and McCloskey 2008; McCloskey and Ziliak 1996).

This movement, while essential for the credibility of scientific research, does not explain what importance means, nor how it should be measured. Accurately measuring importance is however critical, not only for researchers seeking to objectively present their results, but also for policy-makers and medias who might use or refer to the findings. When feasible, cost-benefit analysis is usually the most informative approach to measure economic importance (e.g. for impact evaluations). However, for many research questions, cost-benefit analysis is unworkable because there is no obvious or objective way to define an objective function, or because the costs or benefits do not exist or are too complex to be calculated (e.g. research on the determinants of conflicts, long-run growth, or migration). For such research questions, another approach is required.

This paper studies how to assess importance in regression analysis when cost-benefit analysis is not an option. The contribution of this paper is both methodological and empirical. On the methodological side, I use an axiomatic approach to derive two measures of the importance of regressors and residuals in regressions. Broadly speaking, an explanatory variable in a regression model will be deemed important if it generates a lot of variation, either alone, or jointly with other regressors. On the empirical side, I demonstrate the relevance and complementarity of the two measures in two cases studies, the first one on the causes of wars, and the second one on the deep roots of economic development. I also created a new *Stata* package called *importance*, which estimates the two measures.

The paper proceeds as follows. I first explain why methods currently used to assess the importance of explanatory variables are imperfect and should therefore be avoided.

I then derive the two measures of importance using an axiomatic approach. Both methods aim at measuring the percentage contribution of each explanatory variable to variation in the dependent variable. They differ in how they handle variation induced by explanatory variables that are correlated. In order to introduce these methods and understand their differences, it is useful to consider a simple example. Consider the model $y = x_1 + x_2 + \epsilon$ where x_1, x_2, and $\epsilon \sim N(0, 1)$. The correlation between x_1 and x_2 is equal to 0.5, while ϵ is independent.

The first method focuses on *ceteris paribus* variation that is, the variation generated independently of other variables. In the example, the variance generated independently by each variable and by the error term is equal to 1, as $Var(\beta_1 x_1) = Var(\beta_2 x_2) = Var(\epsilon) = 1$. According to the *ceteris paribus* approach, the importance of each variable and of the error term is equal to 1/3 or 33.3%. In more general models, the importance of a variable x_i is measured as: $q_i^2 = Var(\beta_i x_i)/(Var(\epsilon) + \sum_{j=1}^{n} Var(\beta_j x_j))$. The measure q_i^2 captures the variation generated by the explanatory variable x_i *ceteris paribus* and expresses it in percentage terms. To the best of my knowledge, this method has never been proposed in the literature. I therefore propose a set of reasonable axioms that characterizes the measure.

The second method focuses on *non-ceteris paribus* variation: the importance of an explanatory variable not only depends on the variation it generates alone, but also on the variation co-generated with other explanatory variables. In the example, $Var(\beta_1 x_1 + \beta_2 x_2) = 3$ as x_1 and x_2 are positively correlated. According to the *non-ceteris paribus* approach, the measures of importance of x_1 and x_2 are equal to 3/8 or 37.5% each, while the importance of ϵ is equal to 1/4 or 25%. In more general models, the importance of a variable x_i is measured as: $E_i = \sum_{j=1}^{n} Cov(\beta_i x_i, \beta_j x_j))/Var(y)$. This measure has been discussed in the early literature on importance measurement decades ago (Hoffman 1960; Shorrocks 1982; Pratt 1987). However, it has heavily criticized and disregarded later on because it can lead to negative values. The present paper resuscitates this method by proposing a simplified list of axioms characterizing the measure, and by uncovering a new interpretation of the measure that makes sense of negative values. In particular, I show that the measure E_i can be interpreted as the elasticity of $Var(y)$ with respect to $Var(\beta_i x_i)$.

The two measures are complementary. They bring different information, especially when they sharply differ. If the ceteris paribus importance of a variable is much larger than its non-ceteris paribus importance, it means that the effect of that variable is going against the effects of other variables included in the estimated model. On the contrary, if the ceteris paribus importance of the variable is much smaller than its non-ceteris paribus importance, it means that the effect of that variable is reinforcing the effect of other important variables. It is worth keeping in mind that the two methods rely on the consistent estimation of regressions coefficients and of the variances and covariances of variables. Therefore, researchers should first rule out (or minimize) misspecification and endogeneity problems before assessing variables' importance.

I then apply these methods in two case studies. First, I re-examine the relationship between war and relatedness identified by Spolaore and Wacziarg (2016). This case study was specifically chosen because it relies upon a large dataset of 13,176 country pairs. With large datasets, most differences that are not random are likely to be statistically significant, which is why assessing the importance of findings is essential. Using dyadic data, Spolaore and Wacziarg (2016) show that genetic distance is negatively correlated with a dummy equal to 1 if two countries ever had a conflict, controlling for a series of geographical variables. They conclude that more closely related populations are more prone to engage in international conflict with each other. Using the measures of importance developed in this paper, I find that the statistically significant relationship between genetic distance and inter-state wars is relatively unimportant. Genetic distance explains very little, less than 0.5% of the variance of the four indicators of conflict considered. Perhaps not surprisingly, contiguity and years of coexistence are by far the most important variables explaining inter-state wars. To be sure, I do not conclude that the analysis of Spolaore and Wacziarg (2016) is irrelevant, quite the contrary. Identifying a positive association between the occurrence of interstate conflicts and the degree of relatedness is an important contribution to the conflict literature. It is not because an empirical relationship is unimportant that the research question and the related analysis are irrelevant.

In the second case study, I assess the importance of the determinants of long-run growth. This example was chosen because it illustrates very well the complementarity between the ceteris and non-ceteris paribus measures of importance. The comparative economic development of countries is, to a large extent, explained by a limited set of geographical variables, historical variables, and population characteristics (Nunn 2014; Spolaore and Wacziarg 2013). More than 80 percent of the variation in current GDP per capita (log) is indeed explained in an OLS regression that controls for much-studied variables like malaria ecology, ruggedness, the timing of the Neolithic transition, slave trade intensity, or genetic diversity (table 3, column 1). The literature is however silent on the relative importance of these factors. What percentage of the variation in contemporary development can be attributed to each of these variables? Which factor is both *statistically* and *economically* important?

I estimate a cross-country regression of the log of national income in 2000 on a set of variables that have been extensively discussed in the literature, including malaria ecology (Sachs and Malaney 2002), temperature (Dell et al. 2012), ruggedness (Nunn and Puga 2012), distance to coast (Rappaport and Sachs 2003), the timing of the Neolithic transition (Ashraf and Galor 2011; Putterman 2008; Olsson and Hibbs 2005), slave trade intensity (Nunn 2008), ethnolinguistic fragmentation (Alesina et al. 2003), genetic diversity and its square (Ashraf and Galor 2013), the percentage of the population of European descent (Easterly and Levine 2016; Putterman and Weil 2010), and dummies identifying legal origins (La Porta et al. 2008).

Using the ceteris-paribus measure, I find that legal origin dummies (12.6%), the percentage of the population at risk of malaria (10.1%), and distance to coast (7.2%) are the most important variables explaining current economic development.[1] Religion dummies (6.6%), genetic diversity (3%), and slave trade intensity (3%) are also relatively important. In comparison, the share of the population of European descent (2.5%), the timing of the Neolithic transition (2.2%), ruggedness (1.2%), and ethnolinguistic fragmentation (0.1%) appear to be marginally important.

I also identify important differences between the ceteris paribus and the non-ceteris paribus measures. Theory and the literature are used to explain large discrepancies. For example, the importance of malaria ecology jumps from 10.1% with the ceteris paribus approach to 19.0% with the non-ceteris paribus approach. The importance of slave export intensity and of the share of the population of European descent also rise when the non-ceteris paribus method is considered. The literature shows that Europeans did not settle where fatal diseases like malaria and yellow fever were prevalent (Acemoglu et al. 2001). Rather, they established extractive institutions based on forced work and slavery, which negatively impacted long-run development in affected regions. Where Europeans settled in large numbers, they adopted inclusive institutions which are still fostering economic development today (Acemoglu and Robinson 2013). These mechanisms explain the mutually reinforcing effects of malaria ecology, slave export intensity, and European origins. Similarly, theory and the literature are used to explain why the non-ceteris paribus importance of legal origin dummies is much lower than its ceteris paribus importance.

[1] Regional fixed effects capture 16.2% of the variation.

It is useful to clearly delineate the scope of this research from the onset, in order to manage expectations and anticipate critiques. The methods introduced in this paper do not aim at replacing p-values, standard errors, t-statistics, or regression coefficients. Rigorously estimating sampling error is critical, but very different from measuring importance. Interpreting regression coefficients remains essential to understand the raw effect of explanatory variables on the dependent variable, conditional on other regressors. Regression coefficients and the measures q_i^2 and E_i provide complementary information. Suppose that a research team is studying the causes of unemployment in a population of interest. A dummy identifying individuals suffering from a rare but severe disease would probably have a large regression coefficient, showing that the health condition is likely to cause unemployment for the few people affected. But this dummy would be considered as unimportant according to the measures q_i^2 and E_i because it explains very little variation in the global population. By contrast, a dummy identifying gender would most likely have a smaller coefficient in absolute size, but be identified as much more important according to the measures q_i^2 and E_i. In this sense, the measures q_i^2 and E_i are *more global* than regression coefficients.

The methods described in this paper should not be used to justify the selection of a specific regression model.[2] Instead, the measures q_i^2 and E_i rely on the consistent measurement of regression coefficients, implying that misspecification and endogeneity issues should first be solved before applying the methods. More generally, the methods presented in this paper do not seek to replace human judgement. Human judgement remains essential, for example to derive research hypotheses, to select an identification strategy that minimizes endogeneity and misspecification issues, and to interpret all statistical outputs resulting from analysis.

Importantly, this paper does not address the questions of whether a finding is surprising or new, whether a research is a significant contribution to a field of study, or whether a paper should be published (Andrews and Kasy 2019; Kasy and Frankel 2018). An effect may be deemed important according to the methods

[2]This remark is closely related to the debate on the properties and limits of the R^2 (Krueger and Lewis-Beck 2007; King 1990; Lewis-Beck and Skalaban 1990).

presented in this paper but be of little scientific interest if the results are obvious or if the dependent variable is irrelevant. By contrast, a precise null result may be of great scientific value (Abadie 2018), especially if it challenges a commonly-held view or a theory. It is therefore key to distinguish the *importance of a variable or of an effect in a regression model* from the *importance of a finding or a research in a field of study.* This paper focuses on the former concept. The measures q_i^2 and E_i aim at capturing the importance of the *causal influence* of explanatory variables on the dependent variable (Bring 1995). Regression analysis is all about partial derivatives. Similarly, the measures q_i^2 and E_i relate to the partial derivatives of the dependent variable with respect to explanatory variables. Total derivatives are sometimes more interesting, but also much more difficult to calculate as they require identifying all the causal links between explanatory variables. The metrics q_i^2 and E_i are therefore measuring importance, conditionally on other covariates included in the model.

Why measuring importance? Using credible measures of importance is all the more important given the increasing popularity of "Big Data", with which most variables are expected to be statistically significant. With large datasets, measuring importance is often more relevant than measuring statistical significance. This research therefore contributes to the recent literature on how to improve transparency, reproducibility, and credibility in applied economics (Czibor et al. 2019; Christensen and Miguel 2018; Reed 2018). This literature recognizes that p-value hacking is widespread in economics (Brodeur et al. 2016) because statistically significant results are more likely to be published (Andrews and Kasy 2019; Mervis 2014; Doucouliagos 2005). Different solutions are discussed in the literature, including working with pre-analysis plans (Olken 2015) or split samples (Fafchamps and Labonne 2017), interpreting and publishing null results (Abadie 2018; Franco et al. 2014), taking statistical power seriously (Czibor et al. 2019; Christensen and Miguel 2018), correcting for multiple hypothesis testing (Anderson 2008), and encouraging replication studies and meta-analyzes (Maniadis et al. 2017; Clemens 2017; Camerer et al. 2016).

The present paper also contributes to the literature on variable importance in regression models (see Grömping (2015) for an excellent review), by proposing the new ceteris paribus measure q_i^2, and by proposing a new justification and a new interpretation for the non-ceteris paribus measure E_i. The measure q_i^2 is closely related to the measures α_i^j proposed by Sterck (2019). The research of Sterck (2019) also explores how to measure importance, but it focuses on decomposing deviations instead of the variance of the dependent variable. Typical deviation measures - e.g. the standard deviation or the mean absolute deviation from the mean - have poor additive properties, which complicates the estimation of the importance of the error term. As a result, the measures α_i^j will usually change if an uncorrelated explanatory variable which is part of error term is instead added to the regression model. This property is obviously undesirable: the importance of a variable x_i should not depend on whether uncorrelated explanatory variables are part of the regression model or part of the error term. The remarkable arithmetic properties of the variance and covariance imply that the measures q_i^2 and E_i do not suffer from this problem. The measures q_i^2 and E_i are therefore mathematically more robust and elegant than the measures α_i^j proposed in Sterck (2019). For this reason, I recommend decomposing the variance of the dependent variable, even if studying deviations might sometimes be more intuitive or relevant for policy. The measures discussed in this paper also relates to the literature on decomposition methods in economics, which seeks to decompose the difference in a distributional statistic between two groups into various explanatory factors (see e.g. Fortin et al. (2011) for an excellent review). In contrast to this literature, the present paper does not specifically seek to compare two groups, but rather to compare the importance of all explanatory variables in a single regression model.

The scope of use of the measures q_i^2 and E_i is large, extending beyond applied economics. To be sure, cost-benefit analysis or similar methods should be preferred for research questions with a clear policy objective and measurable costs (e.g. for impact evaluations). However, when cost-benefit analysis is not an option, I recommend using the measures q_i^2 and E_i in order to assess the relative importance of regressors. Of course, these measures should not be applied blindly and in isolation. They are not magic bullets that aim to replace existing statistical methods. Instead, they are complementary tools that describe which variable is generating a lot of variation in a given regression model.

2 Why existing measures of importance are imperfect

The literature abounds with statements about the "importance" of variables of interest. To justify these statements, authors usually report the standardized beta coefficient associated with the variable of interest, or, more rarely, the Shapley value or the partial R^2. I explain why these statistics are inadequate to measure importance. I deduce three criteria that measures of importance should ideally satisfy.

2.1 Standardized beta coefficients

Most economists use standardized beta coefficients to assess the importance of the effects they study. In the long-run growth literature, for example, Spolaore and Wacziarg (2009) report standardized beta coefficients as *"a measure of the magnitude of the coefficients"*. Michalopoulos (2012) reports standardized coefficients to *"facilitate comparison of the quantitative effect across different specifications and across regressors."* In a section entitled *"Economic Magnitude of the Effects"*, Nunn and Puga (2012) report standardized coefficients to prove that *"the differential effect of ruggedness is statistically significant and economically meaningful."* In turn, Alesina et al. (2015) discuss the importance of their findings by noting that the *"standardized beta coefficient of the ethnic inequality index is around 0.20–0.30, quite similar to that of the works on the role of institutions on development (e.g., Acemoglu et al. (2001)."* The economic literature is replete with similar statements.

An important weakness of standardized beta coefficients is that this measure cannot handle categorical variables (e.g. legal origin dummies, such as in La Porta et al. (2008)) or quadratic specifications (e.g. genetic diversity such as in Ashraf and Galor (2013)). For linear specifications, the ratio of the standardized beta coefficients associated with two regressors provides a good measure of their relative importance *within a regression.* The raw standardized beta coefficients are however useless when it comes to comparing importance *across different regression models*, because of two interrelated problems.

The first problem is that standardized beta coefficients do not sum to a number that can be easily interpreted, such as 1, 0, or the R^2. The sum of the standardized beta coefficients can actually be very large - much larger than 1 - if the error term is relatively small and if the number of explanatory variables is large. These conditions are encountered in most empirical studies. In the long-run growth literature, for example, the R^2 of regressions are large and numerous control variables are included in regressions to limit endogeneity issues (table 3, column 1).

The second problem is that standardized beta coefficients are difficult to interpret and compare because they are not bounded and can range anywhere between $-\infty$ and $+\infty$. Take for example the simple data generating process $y = x_1 + x_2$ where x_1 and x_2 are $N(0, 1)$ and ρ_{12} is the coefficient of correlation between x_1 and x_2. The standardized beta coefficients of x_1 and x_2 are approaching 1/2 if ρ_{12} tends to 1, and approaching $+\infty$ if ρ_{12} tends to -1. The fact that the importance of variables can approach infinity is counter-intuitive, especially when it comes to comparison across regressions. And the fact that the importance of x_1 and x_2 is a decreasing function of ρ_{12} seems illogical because the dispersion of y is actually increasing with ρ_{12}.

For these reasons, I argue that raw standardized beta coefficients should not be used to measure importance. But the ratio of standardized beta coefficients can be used to assess the relative importance of continuous variables *within a linear regression.* I conclude that the following criterion should ideally be satisfied by measures of importance:

Criterion 1 (decomposition): *The measures of importance of regressors should be bounded and their sum should be equal to a dimensionless quantity that is easy to interpret (e.g. 1, 0, or the* R^2*).*

2.2 Shapley values

Shapley values divide the R^2 in shares associated with each regressor. To calculate Shapley values, variables are entered one by one in the regression and their marginal contributions to the R^2 are recorded. The Shapley value of a variable is the average of the marginal contributions to the R^2 across all possible permutations of regressors. While quite old (Lindeman 1980; Kruskal 1987), this method has only been adopted recently by empirical economists (Dustmann and Okatenko 2014; Henderson et al. 2018; Manchin and Orazbayev 2018).

The fundamental problem associated with this method is that irrelevant variables may have a large Shapley value if they are correlated with a relevant regressor. By contrast, a relevant variable may have a relatively low Shapley value if it is correlated with irrelevant regressors. This problem occurs even in large sample and in the absence of endogeneity issues. This problem is especially important in the presence of many irrelevant variables that are highly correlated with other regressors. This condition is expected to be satisfied in most empirical studies that are not randomized. In the long-run growth application below, for example, 7 out of the 19 variables included in the regression of table 3 are statistically insignificant, and the absolute value of correlation coefficients between regressors can be very high (maximum = 0.81, average = 0.19). This method should therefore be avoided, even for comparisons *within a regression*. While irrelevant variables may falsely be interpreted as important, relevant ones may be judged unimportant. The following criteria formalize this critique (Grömping 2015).

Criterion 2 (Inclusion and non-negativity): The importance of variables that are relevant in the population model should be positive.

Criterion 3 (Exclusion): The importance of variables that are irrelevant in the population model should be equal to 0.

2.3 Partial r^2

The partial r^2 of a variable measures the proportion of the unexplained variation that is explained by the addition of that variable to the regression. This method has recently been used to assess the importance of genetic diversity in explaining conflict (Arbath et al. 2018) and development (Ashraf and Galor 2013).

The partial r^2 has three problems. First, the sum of partial r^2 is not an easily interpretable number. Even when the R^2 is large, the sum of partial r^2 can be close to 0 if explanatory variables are highly correlated. On the contrary, this sum can be much larger than 1 if explanatory variables are independent and if the R^2 is large. In sum, this measure does not satisfy *Criterion 1*. Second, the partial r^2 of a variable highly correlated with other regressors can be very low even if its regression coefficient is large. This is because the partial r^2 measures the variation exclusively explained by the variable. Consequently, this metric is highly vulnerable to multicollinearity issues. This problem relates to *Criterion 2*. Finally, partial r^2 are highly dependent on which explanatory variables are included in the regression, even if these are independent. This is because the variation exclusively explained by a variable is compared to the mean squared error of the restricted model. The mean squared error is highly dependent on the regressor list. A variable that explains little can have a high partial r^2 if the R^2 is close to 1. This problem relates to *Criterion 3*. Given these problems, partial r^2 should be avoided when assessing importance.

3 How to measure importance

I propose two methods to measure importance. Both approaches aim at decomposing variation in the dependent variable into contributions associated with each explanatory variable and with the error term. They differ in how variation generated by correlated explanatory variables is accounted for.

I consider a vector y, which is the weighted sum of $n+m$ variables: $y = \beta_0 + \sum_{i=1}^{n+m} \beta_i x_i$. Of the $n+m$ variables, n variables are observed and denoted

$x_1, ..., x_n$, while m variables are unobserved, uncorrelated with other explanatory variables, and denoted $x_{n+1}, ..., x_{n+m}$. The number of variables $n+m$ is assumed to be finite. I consider the following regression model:

$$y = \beta_0 + \sum_{i=1}^{n} \beta_i x_i + \epsilon. \tag{1}$$

The error term ϵ is therefore equal to $\sum_{i=n+1}^{n+m} \beta_i x_i$. In line with the literature, the observable parameters of the model are assumed to be consistently estimable, as this research is about importance measurement, but not about endogeneity or sampling issues (Pratt 1987; Kruskal 1987; Bring 1996; Grömping 2007).

The variance of y is given by:

$$Var(y) = \sum_{i=1}^{n} Var(\beta_i x_i) + 2 \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} Cov(\beta_i x_i, \beta_j x_j) + Var(\epsilon). \tag{2}$$

When decomposing the variance of y into contributions v_i associated with each variable and with the error term, it is straightforward that the term $Var(\beta_i x_i)$ should be allocated to the variable x_i. The key challenge is to allocate the terms $2Cov(\beta_i x_i, \beta_j x_j)$ between x_i and x_j for all $j \neq i$.

3.1 A ceteris paribus approach

The first approach focuses on *ceteris paribus* variation that is, the variation generated independently, when other explanatory variables are kept constant. The covariance terms are therefore ignored. The proposed measure of importance captures the *ceteris paribus* variation generated by each explanatory variable and expresses it in percentage terms. The importance of x_i, denoted q_i^2, is measured as:

$$q_i^2 = \frac{Var(\beta_i x_i)}{Var(\epsilon) + \sum_{j=1}^{n} Var(\beta_j x_j)}. \tag{3}$$

The importance of error term is measured as:

$$q_\epsilon^2 = \frac{Var(\epsilon)}{Var(\epsilon) + \sum_{j=1}^{n} Var(\beta_j x_j)}. \tag{4}$$

The parameter $Q_i^2 = 1 - q_\epsilon^2 = \sum_{j=1}^{n} q_1^2$ measures the ceteris paribus importance of observables compared to the importance of all variables of the data generating process. Note that there is a direct relationship between the measure q_i^2 and the standardized beta coefficients of the regression model (denoted b_i^*), as $q_i^2 = b_i^{*2} / \sum_{j=1}^{n} b_j^{*2}$.

Importantly, the measure q_i^2 satisfies the three criteria discussed in section 2. To the best of my knowledge, this approach to measure importance has never been discussed in the literature. I therefore propose a series of axioms characterizing the method.

The first axiom simply states that the measure of importance should express that variation in percentage terms. The fact that standardized beta coefficients and partial R^2 do not add up to a definite number was indeed identified as a key shortcoming of these statistics, which complicate interpretation and limit comparisons across models.

Axiom A.1 - percentage interpretation: *The measure of importance q_i^2 expresses the variation generated by x_i in percentage terms: $q_i^2 = v_i / \sum_{j=1}^{n+m} v_j$.* The measures of importance can therefore be interpreted in percentage terms. An obvious corollary of this axiom is that the sum of the measures of importance is equal to 1: $\sum_{j=1}^{n+m} q_j^2 = 1$.

Axiom A.2 - ceteris paribus: *The variation v_i generated by x_i relates to ceteris paribus effect of x_i on y_i: it measures the variation generated by x_i when* *other variables are kept constant.*

If all variables but x_i are constant, the covariance terms are equal to 0 as the covariance of a variable with a constant term is equal to 0. This axiom therefore implies that the variation v_i generated by x_i only depends on β_i and x_i, and does not depend on the covariance between explanatory variables or on other aspects of their joint distribution.

Axiom A.3 - uncorrelated variables: *If all regressors are uncorrelated with each other, the importance of x_i equal to the R^2 of a simple regression of y on x_i.* The case of uncorrelated variables is *"non-controversial and unique"* (Bring 1996): *"As long as the X's are uncorrelated with each other, the explained variance obviously decomposes into the contributions ${\beta_j}^2 Var(x_j)$, which can be consistently estimated using the unique sums of squares (SS) for each regressor"* (Grömping 2006). The importance of x_i is then given by the ratio ${\beta_j}^2 Var(x_j)/Var(y)$, which is equal to the squared correlation between the dependent variable y and x_i.

It is easy to show that the ceteris paribus measure of importance q_i^2 defined in equation (3) is the unique measure satisfying axioms A.1 to A.3.

Proposition 1 - ceteris paribus importance: *The ceteris paribus measure q_i^2 defined in equation* (3) *is the unique measure satisfying axioms A.1 to A.3. The importance of the residuals is given by equation* (4).

Proof. Proof in appendix A □

3.2 A non-ceteris paribus approach

The second method focuses on *non-ceteris paribus* variation: the importance of an explanatory variable not only depends on the variation it generates alone, but also on the variation co-generated with other explanatory variables. In this approach, the terms $2Cov(\beta_i x_i, \beta_j x_j)$ in equation (2) are therefore considered and split between x_i and x_j.

Without loss of generality, the importance of x_i can be written:[3]

$$E_i = \frac{Var(\beta_i x_i) + \sum_{j \neq i}^{n} w_{ij} 2Cov(\beta_i x_i, \beta_j x_j)}{Var(y)}. \tag{5}$$

In this section, I propose a set of axioms to define the weights w_{ij} such as to split the covariance terms $2Cov(\beta_i x_i, \beta_j x_j)$ between x_i and x_j. The first axiom imposes reasonable limits on the functional form of the weights.[4]

Axiom B.1 - simplifying assumptions: *The weight w_{ij} is a continuous function of the regression coefficients, means, variances, and covariances of variables x_i and x_j. It does not depend on higher moments or other aspects of their marginal or joint distributions. The weight w_{ij} is bounded between 0 and 1 such that $0 \leq w_{ij} = 1 - w_{ji} \leq 1$.*

There are many ways to define the function w_{ij} that satisfy axiom B.1. The simplest one is $w_{ij} = 1/2$, which splits the covariance terms $2Cov(\beta_i x_i, \beta_j x_j)$ equally between x_i and x_j. The resulting measure is actually equivalent to the product measure $b_i^* \rho_{iy}$, where b_i^* is the stantardized beta coefficient of x_i and ρ_{iy} is the simple correlation between x_i and y. This measure was first proposed by Hoffman (1960) and then axiomatized by Pratt (1987). The same measure was constructed by Shorrocks (1982) to decompose inequality into factor components. While the product measure has nice geometric and decomposition properties (Thomas et al. 1998), it has been heavily criticized because it can generate negative values for suppressor variables (Ward Jr 1962; Darlington 1968; Bring 1996; Grömping 2015). Consequently, it does not satisfy the *inclusion and non-negativity criterion* discussed in section 2. The product measure has therefore been mostly disregarded

[3] At this stage, equation (5) entails no loss of generality as no restrictions have been imposed on the weights w_{ij} yet. This becomes clear if w_{ij} is substituted by $w_{ij} = \frac{f_i Var(y)/(n-1) - Var(\beta_i x_i)/(n-1)}{2Cov(\beta_i x_i, \beta_j x_j)}$, in which case $E_i = f_i$, which can literally be anything.

[4] Axiom B.1 assumes that the covariance term associated with x_i and x_j is split between x_i and x_j and that the share attributed to x_i and x_j only depends on the regression coefficients and on the parameters of the joint distribution of x_i and x_j. The continuity assumption seems uncontroversial. The assumption that the quantity of interest depends on the first two moments of the joint distribution is almost always done in the literature, either explicitly or implicitly, in order to simplify the problem at hand (Grömping 2015; Pratt 1987).

in the literature.

I argue that this critique is invalid. It is indeed impossible to define a function w_{ij} that splits the covariance terms such that the importance of variables is always positive for any data generating process. It is impossible to define the weights w_{ij} such that the *inclusion and non-negativity criterion* is satisfied.

Proposition 2 - on negative contributions: *Under axiom B.1, it is impossible to define the weights w_{ij} such that the measure of importance defined in equation (5) is always positive for any β_i, x_i, and $Cov(x_i, x_j)$, $i, j \in 1...n+m$.*

Proof. Proof in appendix A □

The question is therefore not so much how to avoid negative values, as this is impossible under axiom B.1, but rather how to ensure that negative values are meaningful. Instead of imposing that non-ceteris paribus importance cannot be negative, I define an axiom stating when the measure of importance should be negative. This axiom offers an intuitive alternative to the *inclusion and non-negativity criterion.*

Axiom B.2 - negative and positive importance *The non-ceteris paribus importance of x_i is negative if a marginal increase in β_i reduces the variance of y, and positive if a marginal increase in β_i increases the variance of y. The importance of x_i is 0 otherwise.*

Proposition 3 - non-ceteris paribus importance *Only the weights $w_{ij} = 1/2$ satisfy axioms B.1 and B.2 for any β_i, x_i, and $Cov(x_i, x_j)$ with $i, j \in 1...n+m$.*

Proof. Proof in appendix A □

Proposition 3 provides a new justification for the product measure. I also propose a new interpretation of this measure, which is intuitive and hence appealing.

With $w_{ij} = 1/2$, the parameter E_i is the elasticity of the variance of y with respect to the variance of $\beta_i x_i$.[5]

$$
\begin{aligned}
E_i &= \frac{\partial Var(y)}{\partial Var(\beta_i x_i)} \frac{Var(\beta_i x_i)}{Var(y)} \\
&= \frac{Var(\beta_i x_i)}{Var(y)} + \frac{\sum_{j \neq i}^{n} Cov(\beta_i x_i, \beta_j x_j)}{Var(y)}.
\end{aligned} \tag{6}
$$

The sum of the elasticities E_i of regressors is equal to the R^2. In other words, the non-ceteris paribus approach decomposes the R^2 of a regression into shares associated with each explanatory variable.[6] This measure satisfies criteria 1 and 3, but not criterion 2, which has been substituted by Axiom B.2. Importantly, the elasticities E_i should not be interpreted as the "independent contribution of predictors", as originally argued by Hoffman (1962). Instead, the elasticities E_i capture the non-ceteris paribus contribution of explanatory variables, taking into account their covariance with other regressors.

3.3 Complementarity of approaches

The ceteris paribus and non-ceteris paribus methods give the same results if explanatory variables are uncorrelated. The two approaches provide different information when regressors are correlated, which is almost always the case in practice. While the ceteris paribus method measures the relative size of the independent effect of an explanatory variable on the dependent variable, the non-ceteris paribus explicitly considers whether this effect is reinforcing or going against the effects of other correlated variables. Both methods should therefore be interpreted together to provide a comprehensive picture of the importance of explanatory variables in a regression.

The elasticity E_i is composed of two terms. The first one, $Var(\beta_i x_i)/Var(y)$, is a measure of the variance generated independently by x_i. This term is proportional

[5] In order to derive this interpretation, I first rewrite equation (2) as $Var(y) = \sum_{i=1}^{n} Var(\beta_i x_i) + 2\sum_{i=1}^{n-1}\sum_{j=i+1}^{n} \sqrt{Var(\beta_i x_i)}\sqrt{Var(\beta_j x_j)}\rho_{ij} + Var(\epsilon)$ where ρ_{ij} is the correlation between x_i and x_j.

[6] The importance of the error term is therefore given by: $E_\epsilon = Var(\epsilon)/Var(y) = 1 - R^2$.

to the ceteris paribus measure q_i^2. The second term, $\sum_{j \neq i}^{n} Cov(\beta_i x_i, \beta_j x_j)/Var(y)$, captures the variation co-generated with other explanatory variables. If this latter term is positive, it means that the effect of the variable is reinforcing the effect of other explanatory variables on average. On the contrary, if it is negative, it means that the effect of the variable is suppressing the effect of other explanatory variables on average.

For more details, it is useful to analyze the full covariance matrix. A positive covariance term $Cov(\beta_i x_i, \beta_j x_j)/Var(y)$ means that the effects of variables x_i and x_j are reinforcing each other. On the contrary, a negative covariance term means that their effects are canceling out.

A simple example is useful to illustrate and compare the two methods. Consider the model $y = x_1 + x_2 + \epsilon$ where x_1, x_2, and $\epsilon \sim N(0, 1)$. The correlation between x_1 and x_2 is denoted ρ_{12}, while ϵ is independent. I consider three cases in table 1.

In the first case, explanatory variables are uncorrelated, in which case the ceteris paribus and non-ceteris paribus method always give the same results. The importance of each variable is equal to 1/3. The covariance terms are equal to 0.

In the second case, the correlation between x_1 and x_2 approaches 1. The ceteris paribus importance of each variable remains is equal to 1/3. However, the elasticity E_i of x_1 and x_2 is higher than the elasticity of ϵ. Indeed, the effects of x_1 and x_2 are reinforcing each other, which is why their covariance terms are positive.

In the third case, the correlation between x_1 and x_2 approaches -1. The effects of x_1 and x_2 are canceling out, explaining why the measures of importance of x_1 and x_2 drop from 1/3 according to the ceteris paribus approach to 0 according to the non-ceteris paribus approach. By contrast, the importance of ϵ jumps from 1/3 according to the ceteris paribus approach to 1 according to the non-ceteris paribus approach, which makes sense given that $y \approx \epsilon$.

3.4 Remarks

Estimation and confidence intervals Discussing the importance of variables is by no means substitute to solving misspecification and endogeneity issues. The parameters q_i^2 and E_i only depend on the variances and covariances of variables and on the mean squared error, for which consistent estimators are well known. Consistent estimators for q_i^2 and E_i can therefore be easily defined as the empirical analogs of the theoretical quantities defined in equations 3 and 6. The consistency of such estimators simply follows from Slutsky's theorem.[7] The estimators of q_i^2 and E_i will be inconsistent if the estimators of regression coefficients are inconsistent, for example because of omitted variables, reverse causality, misspecification, or mismeasurement problems. Researchers should therefore first solve or minimize misspecification and endogeneity issues before estimating the importance of explanatory variables using the methods developed in this article. For research involving sampling (which is not the case in the applications below), I recommend presenting bootstrap confidence intervals to quantify sampling error (Wooldridge 2010).

IV and non-linear models The methods can be easily adapted to IV regressions or to non-linear functional forms. When calculating the variance and covariance terms associated with a variable x_i and its nonlinear terms ${x_i}^2$,...,${x_i}^l$, all terms should be considered together.[8] Assessing the importance of linear and nonlinear terms separately should be avoided because the contribution of each term would not be invariant to linear transformations of the variable. Invariance to linear transformations is unambiguously seen as desirable in the literature (Pratt 1987; Grömping 2015). Similarly, the methods can also be used to measure the importance of categorical variables. Similar to quadratic terms, all dummies related to a categorical variable should be considered together when estimating variance and covariance terms.

[7]Note that in small samples, the inclusion of irrelevant variables generates a downward bias in the estimated contributions of relevant variables. This small sample bias is also observed for Shapley values and for the partial-R^2.

[8]For example, the variance generated by x_i is given by $Var(\beta_{i1}x_i + \beta_{i2}{x_i}^2 + ... + \beta_{il}{x_i}^l)$.

Partial versus total derivatives In line with regression analysis, the two methods relate to the partial derivatives of the dependent variable with respect to explanatory variables. However, total derivatives are often more interesting, but also much more difficult to calculate as they require identifying all the causal links between explanatory variables. In the presence of bad controls (Angrist and Pischke 2008), partial derivatives can be very different from total derivatives. Problems of bad control should therefore be minimized before applying the methods.

Stata command I have developed a *Stata* package that implements the two methods. The files are available on my personal website.

4 War and relatedness

In this first case study, I re-examine the relationship between war and relatedness identified by Spolaore and Wacziarg (2016). Using a large dyadic dataset of 13,176 country pairs, Spolaore and Wacziarg (2016) find that more closely related populations - as proxied by their genetic distance - are more prone to engage in international conflict with each other.

I consider four dependent variables, which are build using dyadic panel data on interstate conflict between 1816 and 2001 from the Correlates of War Project (Ghosn et al. 2004):[9] (1) a dummy variable equal to 1 if the pair of countries ever had a conflict, (2) the inverse hyperbolic sine of the number of years of conflict, (3) the inverse hyperbolic sine of the number of separate conflicts, and (4) the maximal intensity of conflict on a discrete scale ranging from 0 for no militarized conflict to 5 for an interstate war involving more than 1, 000 total battle deaths.

Genetic distance is used as a proxy to capture relatedness between populations (Spolaore and Wacziarg 2009). In the main analysis, I consider genetic distance between populations as of the year 1500 to minimize the risk of reverse causality.[10] However, I obtain similar results when considering modern genetic distance in

[9] I warmly thank Enrico Spolaore and Romain Wacziarg for sharing their data and dofiles.

[10] In appendix B, I explain why I have a weak preference for this specification.

a OLS regression (table A.3 in Appendix), or when modern genetic distance is instrumented by genetic distance in 1500 (table A.4 in Appendix). I consider all the geographic control variables included in the analysis of Spolaore and Wacziarg (2016). I also control for the number of years each pair of countries coexisted[11] and, when relevant, for the average of countries' characteristics within pairs.[12]

Results of OLS[13] regressions are presented in table 2, alongside the ceteris paribus measure of importance q_i^2 and the non-ceteris paribus elasticities E_i. The covariance matrix $Cov(\beta_i x_i, \beta_j x_j)/Var(y)$ and the correlation matrix ρ_{ij} are shown in appendix (tables A.5 and A.6).

The coefficients of genetic distance are negative and statistically significant at conventional thresholds, in line with the results of Spolaore and Wacziarg (2009). Given the large number of observations in the data, many other variables are statistically significant in all four regressions. Contiguity, sharing an ocean, being large, having had a colonial relationship, years of coexistence, and having a high percentage of fertile soil are characteristics that are positively associated with conflict. Distance, being landlocked and having tropical, desert, or rugged land are negatively associated with conflict. All coefficients have the sign I was expecting.

Results are very different when it comes to importance. I do not distinguish the ceteris and non-ceteris paribus measures when interpreting the results because they give very similar results in this case study.[14] Genetic distance explains very

[11]For example, the US and Croatia coexisted only for 16 years, while the US and France coexisted for 192 years. If time plays a role, the likelihood that there was a ever a conflict between the US and France might be much larger than between the US and Croatia, ceteris paribus.

[12]For geographic characteristics such as ruggedness, % of tropical, fertile, or desert soil, the average of countries' characteristics within pair is likely to matter more than the absolute difference.

[13]While Spolaore and Wacziarg (2009) estimate Probit regressions, I focus on OLS regressions for three reasons. First, three out of the four dependent variables I consider are not binary. Second, economists nowadays tend to prefer the linear probability model (Angrist and Pischke 2008). Third, the ceteris and non-ceteris paribus measures have been developed for linear models (which can include log or quadratic terms or more complex functional forms). Extending these measures to non-linear models such as Probit, Logit, or negative binomial models, is beyond the scope of this paper.

[14]This is because only two variables have large variance terms $Var(\beta_i x_i)/Var(y)$ - contiguity and years of coexistence, and these two variables are not much correlated (coefficient of correlation = 0.07). See tables A.5 and A.6 in appendix for more details.

little, less than 0.5% of the variance of conflict indicators. Contiguity and years of coexistence are by far the most important factors explaining the occurrence, the duration, and the intensity of interstate war. The contiguity dummy explains between 7.1 and 13.3% of the variance of conflict indicators. The number of years of coexistence explains between 7.9 and 10.3% of the variation. The next most important variables relates to countries' sizes and percentage of tropical soil, which explain about 1% of the variation each. Other variables are not important. Despite numerous control variables, the residuals regressions are large, explaining between 70 and 75% of the variation in the dependent variables.[15] This suggests that that time-varying factors, history, and geopolitical dynamics matter more than gravity variables when it comes to explaining conflicts between nations.

This case study illustrates that assessing importance is usually more informative than looking at significance stars, especially with large datasets. To conclude, I emphasize that this case study should not be interpreted as a critique of the work of Spolaore and Wacziarg (2016). First, because Spolaore and Wacziarg (2016) actually measured the importance of their coefficients of interest in standardized-deviation terms, the current best practice in economics. Second, their main conclusion, that relatedness is positively associated with interstate conflicts, remains valid and interesting because it goes against the commonly-held view that ethnic dissimilarity is associated with war and plunder. Finally, I emphasize, in line with Abadie (2018), that insignificant or unimportant relationships are not necessarily uninteresting, quite the contrary.

5 The deep roots of economic development

The study of the long-run causes of comparative economic development is particularly relevant to illustrate the two methods, as the presence of many competing

[15] In order to explore what could drive the unexplained variation, I regressed the residuals on dummies identifying individual countries. For example, the dummy US is equal to one if the US is part of the pair of countries. I find that these dummies explain about 11% of the unexplained variation, that is, about as much as contiguity or number of years of coexistence. A few imperialist countries are responsible for a large part of this, namely Germany, the United States, the United Kingdom, Iraq, France, Italy, and Russia.

predictors of long-term development makes the measurement of their relative importance very relevant. This is the objective of this section.

I estimate a simple OLS regression to analyze the determinants of the logarithm of GDP per capita in 2000. I will focus one specification only, as my objective is to illustrate the two methods, but not to discuss endogeneity and specification issues. Following the literature, I consider 18 explanatory variables that have been identified as important in the literature, and for which data availability is not a problem (data sources are detailed in appendix C.1). To minimize subjectivity when establishing the list of explanatory variables, I focus on variables used by Nunn and Puga (2012) and Ashraf and Galor (2013). I however exclude the variables " social infrastructure" and "years of schooling" which can be considered as bad controls or outcome variables (Angrist and Pischke 2008), as well as the colonizers fixed effects which are multicollinear with the legal origin dummies. I also include regional fixed effects to control for unique regional characteristics (geographical, human, or historical) that are unobserved, but affecting development. It is worth noting that researchers willing to study one specific explanatory variable might prefer a slightly different specification or estimation method, in order to minimize the endogeneity, specification, and bad control issues associated with their variable of interest.

The list of geographical variables includes the percentage of the population at risk of malaria (Sachs and Malaney 2002), the average annual temperature in Kelvin degrees (Dell et al. 2012), the average annual level of precipitation in millimeter, a measure of terrain ruggedness (Nunn and Puga 2012), the average distance to the nearest ice-free coast (Rappaport and Sachs 2003), the percentage of each country with fertile soil (Sokoloff and Engerman 2000), the percentage of tropical land, and desert land, the log of absolute latitude (Sala-i Martin 1997), a variable measuring carats of gem-quality diamonds extracted per square kilometer between 1958 and 2000 (Sachs and Warner 2001), and a dummy identifying OPEC countries.

Historical variables include the log of the number of years since a country transitioned from hunting and gathering to agriculture adjusted for population ancestry (Ashraf and Galor 2011; Putterman 2008; Olsson and Hibbs 2005), a measure of slave trade intensity (Nunn 2008), and legal origin dummies (La Porta et al. 2008).

Population variables include genetic diversity and its square (Ashraf and Galor 2013), ethnolinguistic fragmentation (Alesina et al. 2003), the percentage of the population of European descent (Easterly and Levine 2016; Putterman and Weil 2010), and religion shares (Woodberry 2012; Becker and Woessmann 2009).

The results of the OLS regression are presented in column 1 of table 3. The statistics q_i^2 from the ceteris paribus method are shown in column 2, while the elasticities E_i from the non-ceteris paribus method are shown in column 3. In columns 4 and 5, I decompose the elasticities E_i into variance and covariance contributions, in line with equation (6). The covariance matrix $Cov(\beta_i x_i, \beta_j x_j)/Var(y)$ and the correlation matrix ρ_{ij} are shown in appendix (tables A.7 and A.8). These matrices are useful to compare the results of the two methods and interpret differences. A general overview of table 3 shows that the predictive power of the estimated model is large: the R^2 is equal to 84.4%. Regional fixed effects capture a substantial part of the variation in contemporary development.

The most important geographical variable ceteris paribus is the percentage of the population at risk of malaria (10.1%), which has a negative impact on economic development (Sachs and Malaney 2002). The average distance to the nearest ice-free coast is the second most important geographic variable according to the ceteris paribus method. Being close to the coast is positively associated with development (Rappaport and Sachs 2003). This variable explains 7.2% of ceteris paribus variations in the log of GDP per capita. Three other geographical variables are statistically significant at conventional thresholds but their importance is more limited: the OPEC dummy (2.4%) which is associated with higher GDP per capita, terrain ruggedness (1.2%) which negatively affects development (Nunn and Puga 2012), and the percentage of each country with fertile soil (1.1%) which is negatively associated with contemporary development (Sokoloff and Engerman 2000). The average temperature, the average level of precipitation, the log of absolute latitude, the percentage of tropical land, the percentage of desert, and the measure of diamonds extraction are insignificant at conventional levels, and their importance appears to be minor.

The legal origin of countries appears to be the most important factor explaining contemporary development ceteris paribus (12.6%). Legal origin dummies are jointly significant (F-test p-value = 0.00) (La Porta et al. 2008). Compared to countries with French civil law origins, countries with common law or German civil law origins are richer today, while countries from socialist legal tradition are poorer ceteris paribus. In line with expectations, the coefficient of slave trade intensity is negative and statistically significant at conventional thresholds (Nunn 2008). The ceteris paribus importance of this variable is moderate (3%). The coefficient of the number of years since the Neolithic transition (log) is positive and statistically significant (Ashraf and Galor 2011; Putterman 2008; Olsson and Hibbs 2005), but the ceteris paribus importance of this variable is comparatively low (2.2%).

Religion shares are jointly statistically significant (F-test p-value = 0.04) and their importance is equal to 6.6%. In line with the literature, the indicator of genetic diversity and its square are jointly significant at the 1% threshold (Ashraf and Galor 2013). The ceteris paribus importance of this variable is moderate (3%). The percentage of the population of European descent has a positive and statistically significant effect on contemporary development (Easterly and Levine 2016; Putterman and Weil 2010). The ceteris paribus importance of this variable is modest (2.5%). Ethnolinguistic fragmentation is not statistically significant and appears to be unimportant (0.1%) (Alesina et al. 2003).

Overall, the ceteris paribus method leads to nuanced conclusions about the importance of the different explanatory variables included in the estimated model. No single variable stands out unambiguously as the key determinant of long-term growth. Results shows that contemporary development of countries is explained by a multitude of geographical and historical factors, as well as by the composition of their population. The ceteris paribus contribution of each of these factors never exceeds 13%.

There are interesting differences between the ceteris paribus and the non-ceteris paribus measures. Theory and the literature can be used to explain large discrepancies. An interesting example relates to the reinforcing effects of malaria ecology, of slave export intensity, and of the share of the population of European descent. The resulting non-ceteris paribus importance of these variables is very high: 19.0%, 8.7%, and 8.1% respectively. The average of covariance terms associated with these variables are positive and large (column 5). The literature shows that Europeans did not settle where fatal diseases like malaria and yellow fever were prevalent (Acemoglu et al. 2001). Instead, they introduced extractive institutions based on forced work and slavery, which negatively impacted long-term growth. Where they settled in large numbers, Europeans adopted inclusive institutions whose benefits are still visible today (Acemoglu and Robinson 2013). These mechanisms are observed in the data. Malaria and slave export intensity are strongly and positively correlated (coefficient of correlation = 0.76), and both variables have a large negative impact on contemporary development ceteris paribus. By contrast, malaria and the share of the population of European descent are negatively correlated (coefficient of correlation = -0.56), and the regression coefficient of this latter variable is negative. Therefore, the covariance terms of these variables are positive and large (table A.7): the effects of malaria ecology, of slave export intensity, and of the share of the population of European descent are mutually reinforcing.

These three variables are also strongly correlated with the sub-Saharan Africa dummy (coefficients of correlation = 0.81, 0.79, and -0.47 respectively). The measures of slave export intensity and of malaria risk are particularly large in sub-Saharan Africa, while relatively few Europeans settled there. The coefficient associated with the sub-Saharan Africa dummy is negative and large, suggesting that unobserved characteristics are, on average, not favorable to comparative development in sub-Saharan Africa. Region fixed effects are therefore magnifying the non-ceteris paribus importance of malaria ecology, of slave export intensity, and of the share of the population of European descent.

The non-ceteris paribus importance of the timing of the Neolithic transition (6.5%) is also much larger than its ceteris paribus importance (2.2%). The effect of this variable also goes hands in hands with the effect of malaria risk and with the sub-Saharan Africa dummy. This can be explained by the strong connection between bio-geographic conditions and the timing of the Neolithic transition (Ashraf and Galor 2011; Putterman 2008; Olsson and Hibbs 2005). The number of years since the Neolithic transition is negatively correlated with the share of the population at risk of malaria (coefficient of correlation = -0.65) and with the sub-Saharan Africa dummy (coefficient of correlation = -0.77). The regression coefficient of the number of years since the Neolithic transition is positive, while the regression coefficients of the share of the population at risk of malaria and of the sub-Saharan Africa dummy are negative. Therefore, the covariance terms of these variables are positive and large (table A.7): the effects of the timing of the Neolithic transition, of malaria risk and regional fixed effects on contemporary development are mutually reinforcing.

Another interesting example relates to the non-ceteris paribus importance of legal origin dummies (3.1%), which is sharply reduced compared to its ceteris paribus importance (12.6%). Socialist law is negatively associated with contemporary development. Out of the 35 countries that adopted socialist law, 27 are in Europe or Central Asia, a region which is on average more developed than the rest of the World. The variation generated by the legal origin dummies and the variation generated by the regional fixed effects are therefore partially canceling out. Furthermore, socialist countries are, on average, characterized by low malaria burden, no slave trade history, and a high share of population of European descent. The effect of socialist law is going against the effects of these important variables, which is why its importance is diminished according to the non-ceteris paribus approach.

Finally, the importance of ruggedness drops from 1.2% with the ceteris paribus approach to 0.2% with the non-ceteris paribus approach. The average of covariance terms associated with ruggedness are indeed negative (column 5). On the one hand, ruggedness is associated with lower national income ceteris paribus. On the other hand, rugged terrain offered a protection from slave raiders during the slave trades (Nunn and Puga 2012), and the slave trades did have a negative impact on the economic development of affected regions within Africa (Nunn 2008). Similarly, ruggedness is associated with lower malaria prevalence, a variable which is negatively correlated with current economic development (Sachs and Malaney 2002). The sum of these opposite effects is small, which explains why the non-ceteris paribus importance of ruggedness is negligible. These examples illustrate the complementarity between the two methods.

6 Conclusion

As research analyzing large datasets is more and more frequent, evaluating the importance of effects is becoming as - if not more - critical than searching for significance stars. This is particularly true for sensitive research questions and findings, which can be misinterpreted by other scholars, by policy-makers, or by the medias.

This research proposed two intuitive methods to measure importance that usefully complement standard measures of statistical significance. According to these methods, an explanatory variable is deemed important if it generates a lot of variation. While the ceteris paribus approach focuses on the variation generated by each explanatory variable separately, the non-ceteris paribus approach also considers the variation co-generated with other explanatory variables. This latter measure can be interpreted as an elasticity. The two methods are complementary: large discrepancies between their results reflect reinforcement or attenuation effects that should be explained using theory. To be sure, the two methods are not substitute to rigorous statistical inference. In fact, they both rely on the consistent estimation of regressions coefficients and of variables' variances and covariances. Therefore, researchers should first rule out (or minimize) problems resulting from model misspecification, omitted variables, reverse causality, and mismeasurement before assessing variables' importance. Still, the scope of use of the two methods is enormous, extending beyond applied economics. When cost-benefit analysis is impossible, I recommend using and comparing the two methods discussed in this paper.

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Table 1 – Simple example: $y = x_1 + x_2 + \epsilon$ with x_1, x_2, and $\epsilon \sim N(0,1)$ and $\rho_{1\epsilon} = \rho_{2\epsilon} = 0$

	β_i (1)	q_i^2 (2)	E_i (3)	$\frac{Var(\beta_i x_i)}{Var(y)}$ (4)	$\frac{\sum_{j \neq i} Cov(\beta_i x_i, \beta_j x_j)}{Var(y)}$ (5)
Case 1: $\rho_{12} = 0$					
x_1	1	1/3	1/3	1/3	0
x_2	1	1/3	1/3	1/3	0
ϵ	1	1/3	1/3	1/3	0
Case 2: $\rho_{12} \approx 1$					
x_1	1	1/3	2/5	1/5	1/5
x_2	1	1/3	2/5	1/5	1/5
ϵ	1	1/3	1/5	1/5	0
Case 3: $\rho_{12} \approx -1$					
x_1	1	1/3	0	1	-1
x_2	1	1/3	0	1	-1
ϵ	1	1/3	1	1	0
R^2	100 %				
Q^2		100 %			

Regression coefficients are presented in column 1. The statistics q_i^2 from the ceteris paribus method are shown in column 2. The elasticities E_i from the non-ceteris paribus method are shown in column 3. In columns 4 and 5, I decompose the elasticities E_i into the variance and covariance contributions, in line with equation (6).

Table 2 – Importance of the correlates of war

	Ever a conflict			Years of conflict (ihs)			Number of conflicts (ihs)			Intensity		
	β_i	q_i^2	E_i	β_i	q_i^2	E_i	β_i	q_i^2	E_i	β_i	q_i^2	E_i
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Fst genetic distance (1500)	-0.079***	0.075	0.446	-0.097*	0.026	0.256	-0.070*	0.026	0.268	-0.304***	0.059	0.391
	(0.025)			(0.051)			(0.036)			(0.108)		
Log geodesic distance	-0.017**	0.341	1.215	-0.029*	0.235	1.022	-0.032***	0.562	1.693	-0.068**	0.305	1.130
	(0.007)			(0.015)			(0.011)			(0.029)		
Log absolute difference in longitudes	-0.001	0.005	0.095	-0.003	0.004	0.083	0.002	0.006	-0.101	-0.006	0.006	0.094
	(0.003)			(0.007)			(0.005)			(0.015)		
Log absolute difference in latitudes	-0.009***	0.190	0.472	-0.020***	0.213	0.533	-0.012***	0.144	0.462	-0.041***	0.202	0.481
	(0.002)			(0.005)			(0.003)			(0.010)		
1 for contiguity	0.455***	7.456	8.929	1.141***	10.823	12.170	0.865***	11.882	13.277	1.927***	7.112	8.576
	(0.032)			(0.087)			(0.065)			(0.135)		
Number of landlocked countries in the pair	-0.026***	0.408	0.498	-0.057***	0.456	0.532	-0.044***	0.528	0.589	-0.120***	0.476	0.544
	(0.005)			(0.010)			(0.007)			(0.022)		
Number of island countries in the pair	0.033***	0.614	-0.598	0.070***	0.651	-0.606	0.043***	0.476	-0.547	0.156***	0.756	-0.647
	(0.004)			(0.009)			(0.006)			(0.020)		
1 if pair shares at least one sea or ocean	0.038***	0.252	0.713	0.086***	0.301	0.814	0.074***	0.426	1.065	0.149***	0.209	0.628
	(0.009)			(0.020)			(0.015)			(0.039)		
Log product of land areas in square km	0.007***	0.950	1.633	0.013***	0.888	1.624	0.008***	0.602	1.319	0.029***	0.937	1.662
	(0.001)			(0.002)			(0.001)			(0.004)		
1 for pairs ever in colonial relationship	0.107***	0.285	0.552	0.191***	0.209	0.461	0.155***	0.263	0.552	0.418***	0.230	0.473
	(0.031)			(0.065)			(0.050)			(0.130)		
1 if countries were or are the same country	0.044	0.035	0.246	0.014	0.001	0.038	-0.018	0.002	-0.066	0.206	0.041	0.266
	(0.039)			(0.091)			(0.065)			(0.166)		
Years of coexistence	0.002***	7.911	9.346	0.004***	8.331	9.838	0.003***	8.813	10.271	0.008***	8.425	9.873
	(0.000)			(0.000)			(0.000)			(0.000)		
Major oil producer dummy	0.011**	0.052	0.200	0.023***	0.052	0.202	0.022***	0.091	0.281	0.044**	0.046	0.190
	(0.004)			(0.009)			(0.006)			(0.019)		
Ruggedness (abs. dif.)	0.006	0.021	-0.019	0.014**	0.036	-0.013	0.010**	0.031	-0.012	0.021	0.027	-0.003
	(0.004)			(0.007)			(0.005)			(0.015)		
Ruggedness (mean)	-0.011**			-0.030***			-0.020***			-0.053**		
	(0.005)			(0.010)			(0.007)			(0.022)		
% tropical area (abs. dif.)	-0.000	0.994	1.285	-0.000	1.137	1.419	-0.000	0.856	1.165	-0.000	1.197	1.521
	(0.000)			(0.000)			(0.000)			(0.000)		
% tropical area (mean)	-0.001***			-0.002***			-0.001***			-0.003***		
	(0.000)			(0.000)			(0.000)			(0.000)		
% fertile soil (abs. dif.)	-0.000	0.061	-0.034	0.000	0.091	-0.063	-0.000	0.104	-0.048	0.000	0.066	-0.061
	(0.000)			(0.000)			(0.000)			(0.000)		
% fertile soil (mean)	0.000***			0.001***			0.001***			0.001***		
	(0.000)			(0.000)			(0.000)			(0.000)		
% desert area (abs. dif.)	0.000	0.390	0.111	0.002*	0.481	0.123	0.001*	0.388	0.085	0.002	0.452	0.129
	(0.001)			(0.001)			(0.001)			(0.002)		
% desert area (mean)	-0.002**			-0.007***			-0.005***			-0.012***		
	(0.001)			(0.002)			(0.002)			(0.004)		
Avg. distance to coast (abs. dif.)	0.008	0.149	0.083	0.045	0.287	0.103	0.038*	0.492	0.190	0.037	0.179	0.109
	(0.013)			(0.028)			(0.021)			(0.056)		
Avg. distance to coast (mean)	0.020			0.026			0.032			0.100		
	(0.025)			(0.057)			(0.042)			(0.108)		
% within 100 km. of ice-free coast (abs. dif.)	0.000	0.006	-0.044	-0.000	0.005	-0.034	-0.000	0.012	-0.047	0.000	0.000	-0.011
	(0.000)			(0.000)			(0.000)			(0.000)		
% within 100 km. of ice-free coast (mean)	0.000			0.000			0.000			0.000		
	(0.000)			(0.000)			(0.000)			(0.001)		
Observations	13176			13176			13176			13176		
R^2	0.251			0.285			0.304			0.253		

Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3 – Long-run growth regressions

	Dependent variable: GDP per capita in 2000 (log)				
	β_i	q_i^2	E_i	$\frac{Var(\beta_i x_i)}{Var(y)}$	$\frac{\sum_{j\neq i} Cov(\beta_i x_i, \beta_j x_j)}{Var(y)}$
	(1)	(2)	(3)	(4)	(5)
% of pop. at risk of malaria	-0.87***	10.07	18.96	7.05	11.90
	(0.32)				
Avg. annual temp (K)	-0.01	0.14	1.36	0.10	1.26
	(0.02)				
Avg. annual precipitation (mm)	-0.00	2.90	2.01	2.03	-0.02
	(0.00)				
Ruggedness	-0.10*	1.24	0.19	0.87	-0.68
	(0.05)				
Avg. Distance to coast	-0.74***	7.22	7.16	5.06	2.10
	(0.20)				
% of fertile soil	-0.53*	1.09	-0.40	0.76	-1.16
	(0.29)				
% of tropical land	-0.08	0.09	0.97	0.06	0.91
	(0.30)				
% of desert	0.32	0.11	-0.02	0.08	-0.10
	(0.49)				
Absolute latitude (log)	-0.10	0.74	-3.20	0.52	-3.72
	(0.13)				
Diamonds (carats)	0.00	0.08	-0.21	0.05	-0.27
	(0.00)				
OPEC dummy	0.63**	2.44	2.04	1.71	0.33
	(0.26)				
Neolithic transition (adj. & log)	0.38*	2.19	6.49	1.54	4.96
	(0.22)				
Slave export intensity (log)	-0.08*	3.04	8.67	2.13	6.54
	(0.04)				
Ethnolinguistic fragmentation	0.14	0.09	-1.23	0.07	-1.30
	(0.29)				
% European descent	0.44*	2.53	8.05	1.77	6.28
	(0.26)				
Predicted genetic diversity (ancestry adjusted)	291.04***	3.05	4.97	2.13	2.83
	(95.73)				
Predicted genetic diversity squared	-205.69***				
	(68.41)				
% Roman Catholics	0.37	6.59	5.25	4.62	0.63
	(0.43)				
% Muslims	-0.57				
	(0.50)				
% other religions	-0.05				
	(0.47)				
Common law	0.26*	12.56	3.09	8.80	-5.71
	(0.15)				
Socialist law	-0.78***				
	(0.18)				
German civil law	0.85***				
	(0.26)				
Scandinavian law	0.39				
	(0.41)				
East Asia and Pacific region dummy	-0.29	16.24	20.29	11.37	8.91
	(0.29)				
Latin America and Caribbean region dummy	-0.82***				
	(0.26)				
Middle East and North Africa region dummy	-0.27				
	(0.26)				
North America region dummy	0.58**				
	(0.27)				
South Asia region dummy	-1.68***				
	(0.37)				
Sub-Saharan Africa region dummy	-0.88**				
	(0.35)				
Observations	155				
R^2	0.844				
Q^2		72.4 %			

OLS regression coefficients are presented in column 1, with robust standard errors in parentheses. The statistics q_i^2 from the ceteris paribus method are shown in column 2. The elasticities E_i from the non-ceteris paribus method are shown in column 3. In columns 4 and 5, I decompose the elasticities E_i into the variance and covariance contributions, in line with equation (6). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Online Appendix

A Mathematical proofs

Proposition 1 - ceteris paribus importance: *The ceteris paribus measure* q_i^2 *defined in equation* (3) *is the unique measure satisfying axioms A.1 to A.3.*

Proof. From axiom 3, we have that v_i is equal to $Var(\beta_i x_i)$ in the case of uncorrelated regressors. Because v_i cannot depend on the covariance between regressors (Axiom 2), v_i must also be equal to $Var(\beta_i x_i)$ in the case of correlated regressors. From Axiom 1, we have that the importance of x_i is equal to:

$$q_i^2 = \frac{Var(\beta_i x_i)}{\sum_{j=1}^{n+m} Var(\beta_j x_j)}.$$

Because variables in the error term are uncorrelated by assumption, $\sum_{j=n+1}^{n+m} Var(\beta_j x_j) = Var(\epsilon)$. □

Proposition 2 - on negative contributions: *Under axiom B.1, it is impossible to define the weights* w_{ij} *such that the measure of importance defined in equation* (5) *is always positive for any* β_i, x_i, *and* $Cov(x_i, x_j)$, $i, j \in 1...n+m$.

Proof. To demonstrate the impossibility, I simply find a data generating process for which there is always a variable with negative importance, whatever the functional form of w_{ij}. Consider $y = x_1 + x_2 + x_3$ where x_1, x_2, and x_3 are distributed as $N(0,1)$ and $Cov(x_1, x_2) = -Cov(x_1, x_3) = -Cov(x_2, x_3) = \alpha$. Because $w_{ij} = 1 - w_{ji}$, and because variables have the same mean and variance, we must have $w_{12} = w_{21} = 1/2$, $w_{13} = w_{31} = 1/2$, and $w_{23} = w_{32} = 1/2$. We obtain that E_3 is negative as long as $\alpha > 1/2$. □

Proposition 3 - non-ceteris paribus importance *Only the weights* $w_{ij} = 1/2$ *satisfy axioms B.1 and B.2 for any* β_i, x_i, *and* $Cov(x_i, x_j)$ *with* $i, j \in 1...n+m$.

Proof. As w_{ij} does not depend on n and as Proposition 3 must be true for any n, then the proof of Proposition 3 can focus on the case $n = 2$. If E_i and $\partial Var(y)/\partial\beta_i$ have the same sign, they must be equal to 0 for the same values of parameters.

$$\begin{cases} E_1 = 0 \Leftrightarrow Cov(\beta_1 x_1, \beta_2 x_2) = \dfrac{-Var(\beta_1 x_1)}{2w_{12}} & (7) \\ \dfrac{\partial Var(y)}{\partial \beta_1} = 0 \Leftrightarrow Cov(\beta_1 x_1, \beta_2 x_2) = -Var(\beta_1 x_1) & (8) \end{cases}$$

We therefore have $\frac{-Var(\beta_1 x_1)}{2w_{12}} = -Var(\beta_1 x_1) \Leftrightarrow w_{12} = \frac{1}{2}$.

□

B Appendix related to Section 4

B.1 Modern genetic distance versus genetic distance in 1500

Two measures of genetic distance are available, one based on population data from around the 1990s, and the other based on population data from 1500, before modern explorations and migrations. For various reasons, I have a weak preference for the measure of genetic distance in 1500.

1. It seems clear that genetic diversity around 1990 cannot have influenced conflicts between 1816 and 1990. From a logical point of view, the measure of genetic diversity should precede conflict data.

2. Using the first measure could lead to reverse causality bias. Both measures could be affected by mismeasurement problems, leading to attenuation bias. Attenuation bias is usually preferable to reverse causality bias because it leads to more prudent estimates.

3. In columns 1 to 4 of table A.1, both measures are introduced in the regressions. Genetic diversity as of the year 1500 seems to more consistently capture the negative relationship between genetic distance and conflict.

4. When modern genetic diversity is considered alone, coefficients are not significant and signs are inconsistent (table A.3).

5. A simple OLS regression suggests that $gd_{1990} \approx 0.63 gd_{1500} + u$ ($R^2 = 0.52$), where genetic distance in year i is denoted gd_i (column 5 of table A.1). The best measure of genetic distance would be based on population data from around 1800 (before 1816, to avoid reverse causality, but as close as possible from 1816 to best capture the relationship). It seems plausible to assume that $gd_{1800} \approx 0.8 gd_{1500} + v$. Based on these equation, I ran a simple simulation to explore which specification is less likely to be biased. I consider 10,000 observations, and generated the following normal variables:

    - $gd_{1500} \approx N(0, 1)$

- $u \approx N(0, 1)$
- $v \approx N(0, 1)$
- $\epsilon \approx N(0, 1)$
- $gd_{1800} = 0.8gd_{1500} + 0.6v \approx N(0, 1)$
- $gd_{1990} = 0.8gd_{1800} + 0.6u \approx N(0, 1)$
- $y = -gd_{1800} + \epsilon \approx N(0, 2)$.

Results are shown in table A.2. As expected, the coefficients of both gd_{1990} and gd_{1990} are affected by attenuation bias. The IV estimator overestimates the magnitude of the effect of gd_i on y. When I add reverse causality to the data generating process, I find that coefficients of OLS and IV are very unstable, especially when the direction of the reverse causality goes in the opposite direction compared to the studied effect.

Table A.1 – Comparing the measures of genetic distance

	Ever a conflict	Years of conflict (ihs)	Number of conflicts (ihs)	Intensity	Modern genetic distance	
	(1)	(2)	(3)	(4)	(5)	(6)
Genetic distance as of 1500	-0.097***	-0.190***	-0.142***	-0.401***	0.626***	0.544***
	(0.030)	(0.060)	(0.043)	(0.127)	(0.005)	(0.008)
Modern genetic distance	0.029	0.164**	0.132***	0.161		
	(0.034)	(0.067)	(0.047)	(0.148)		
Constant	-0.009	-0.077	0.044	-0.056	0.034***	-0.080***
	(0.050)	(0.109)	(0.077)	(0.219)	(0.001)	(0.008)
Control variables	Yes	Yes	Yes	Yes	No	Yes
Observations	13033	13033	13033	13033	13175	13033
R^2	0.251	0.284	0.303	0.253	0.523	0.577

Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.2 – Monte-Carlo simulation

	gd_{1990} OLS (1)	y OLS (2)	y OLS (3)	y OLS (4)	y IV (5)
gd_{1500}	0.645***			-0.800***	
	(0.008)			(0.012)	
gd_{1800}		-1.001***			
		(0.010)			
gd_{1990}			-0.787***		-1.241***
			(0.012)		(0.020)
Constant	0.003	-0.012	-0.017	-0.017	-0.013
	(0.008)	(0.010)	(0.012)	(0.012)	(0.013)
Observations	10000	10000	10000	10000	10000
R^2	0.412	0.493	0.309	0.317	0.206

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

B.2 Supplementary tables

Table A.3 – Importance of the correlates of inter-state wars (OLS regression)

	Ever a conflict			Years of conflict (ihs)			Number of conflicts (ihs)			Intensity		
	β_i	q_i^2	E_i	β_i	q_i^2	E_i	β_i	q_i^2	E_i	β_i	q_i^2	E_i
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Fst genetic distance (1990)	-0.035	0.011	0.173	0.038	0.003	-0.087	0.037	0.006	-0.122	-0.105	0.005	0.120
	(0.029)			(0.057)			(0.040)			(0.126)		
Log geodesic distance	-0.021***	0.523	1.510	-0.038**	0.415	1.364	-0.040***	0.854	2.095	-0.085***	0.478	1.418
	(0.006)			(0.015)			(0.011)			(0.028)		
Log absolute difference in longitudes	-0.001	0.003	0.069	-0.000	0.000	0.011	0.004	0.019	-0.185	-0.004	0.002	0.061
	(0.003)			(0.008)			(0.005)			(0.015)		
Log absolute difference in latitudes	-0.009***	0.188	0.479	-0.020***	0.206	0.533	-0.012***	0.135	0.455	-0.041***	0.198	0.485
	(0.002)			(0.005)			(0.004)			(0.010)		
1 for contiguity	0.450***	7.258	8.763	1.132***	10.583	11.986	0.856***	11.558	13.034	1.902***	6.901	8.395
	(0.032)			(0.088)			(0.065)			(0.135)		
Number of landlocked countries in the pair	-0.025***	0.397	0.494	-0.057***	0.459	0.538	-0.044***	0.525	0.593	-0.119***	0.466	0.543
	(0.005)			(0.010)			(0.007)			(0.022)		
Number of island countries in the pair	0.033***	0.633	-0.610	0.071***	0.667	-0.617	0.044***	0.488	-0.556	0.159***	0.776	-0.658
	(0.004)			(0.009)			(0.006)			(0.020)		
1 if pair shares at least one sea or ocean	0.036***	0.235	0.683	0.084***	0.289	0.792	0.072***	0.407	1.035	0.144***	0.193	0.599
	(0.009)			(0.020)			(0.015)			(0.039)		
Log product of land areas in square km	0.007***	0.995	1.682	0.014***	0.899	1.646	0.008***	0.599	1.326	0.029***	0.978	1.709
	(0.001)			(0.002)			(0.001)			(0.004)		
1 for pairs ever in colonial relationship	0.103***	0.259	0.518	0.175***	0.174	0.408	0.146***	0.231	0.507	0.400***	0.209	0.444
	(0.031)			(0.064)			(0.049)			(0.130)		
1 if countries were or are the same country	0.045	0.037	0.257	0.018	0.001	0.050	-0.014	0.001	-0.052	0.215	0.045	0.279
	(0.039)			(0.091)			(0.065)			(0.166)		
Years of coexistence	0.002***	8.026	9.461	0.004***	8.501	9.992	0.003***	9.021	10.461	0.008***	8.549	9.994
	(0.000)			(0.000)			(0.000)			(0.000)		
Major oil producer dummy	0.011**	0.049	0.192	0.023**	0.052	0.198	0.022***	0.094	0.281	0.043**	0.044	0.182
	(0.004)			(0.009)			(0.006)			(0.019)		
Ruggedness (abs. dif.)	0.006*	0.022	-0.027	0.015**	0.035	-0.017	0.010**	0.033	-0.011	0.024	0.026	-0.012
	(0.004)			(0.007)			(0.005)			(0.016)		
Ruggedness (mean)	-0.011**			-0.030***			-0.021***			-0.053**		
	(0.005)			(0.010)			(0.008)			(0.023)		
% tropical area (abs. dif.)	-0.000	1.037	1.309	-0.000	1.236	1.490	-0.000	0.945	1.235	-0.000	1.251	1.556
	(0.000)			(0.000)			(0.000)			(0.000)		
% tropical area (mean)	-0.001***			-0.002***			-0.001***			-0.003***		
	(0.000)			(0.000)			(0.000)			(0.000)		
% fertile soil (abs. dif.)	-0.000	0.055	-0.043	0.000	0.089	-0.070	-0.000	0.104	-0.054	0.000	0.062	-0.070
	(0.000)			(0.000)			(0.000)			(0.000)		
% fertile soil (mean)	0.000***			0.001***			0.001***			0.001***		
	(0.000)			(0.000)			(0.000)			(0.000)		
% desert area (abs. dif.)	0.000	0.404	0.117	0.002*	0.492	0.133	0.001*	0.401	0.095	0.003	0.468	0.136
	(0.001)			(0.001)			(0.001)			(0.002)		
% desert area (mean)	-0.003***			-0.008***			-0.005***			-0.013***		
	(0.001)			(0.002)			(0.002)			(0.004)		
Avg. distance to coast (abs. dif.)	0.009	0.145	0.077	0.047*	0.287	0.098	0.039*	0.497	0.191	0.038	0.176	0.104
	(0.013)			(0.028)			(0.021)			(0.056)		
Avg. distance to coast (mean)	0.019			0.024			0.032			0.096		
	(0.025)			(0.057)			(0.042)			(0.108)		
% within 100 km. of ice-free coast (abs. dif.)	0.000	0.017	-0.061	-0.000	0.011	-0.044	-0.000	0.023	-0.060	-0.000	0.004	-0.029
	(0.000)			(0.000)			(0.000)			(0.000)		
% within 100 km. of ice-free coast (mean)	0.000			0.000			0.000			0.000		
	(0.000)			(0.000)			(0.000)			(0.001)		
Observations	13033			13033			13033			13033		
R^2	0.250			0.284			0.303			0.253		

Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.4 – Importance of the correlates of inter-state wars (IV regression)

	Ever a conflict			Years of conflict (ihs)			Number of conflicts (ihs)			Intensity		
	β_i	q_i^2	E_i	β_i	q_i^2	E_i	β_i	q_i^2	E_i	β_i	q_i^2	E_i
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Fst genetic distance (1990)	-0.148***	0.200	0.735	-0.185**	0.071	0.422	-0.129*	0.067	0.422	-0.575***	0.159	0.656
	(0.047)			(0.094)			(0.067)			(0.200)		
Log geodesic distance	-0.014**	0.252	1.045	-0.026	0.189	0.919	-0.030***	0.504	1.603	-0.059*	0.230	0.981
	(0.007)			(0.016)			(0.012)			(0.031)		
Log absolute difference in longitudes	-0.003	0.030	0.223	-0.005	0.015	0.155	0.001	0.000	-0.028	-0.014	0.026	0.203
	(0.004)			(0.008)			(0.006)			(0.016)		
Log absolute difference in latitudes	-0.010***	0.203	0.496	-0.021***	0.221	0.551	-0.012***	0.148	0.474	-0.042***	0.213	0.502
	(0.002)			(0.005)			(0.004)			(0.010)		
1 for contiguity	0.450***	7.309	8.771	1.132***	10.663	11.995	0.856***	11.664	13.044	1.904***	6.952	8.403
	(0.032)			(0.088)			(0.065)			(0.135)		
Number of landlocked countries in the pair	-0.025***	0.386	0.487	-0.056***	0.449	0.531	-0.043***	0.515	0.585	-0.118***	0.456	0.535
	(0.005)			(0.010)			(0.007)			(0.022)		
Number of island countries in the pair	0.033***	0.628	-0.606	0.070***	0.663	-0.613	0.043***	0.485	-0.553	0.158***	0.771	-0.655
	(0.004)			(0.009)			(0.006)			(0.020)		
1 if pair shares at least one sea or ocean	0.036***	0.236	0.684	0.084***	0.291	0.792	0.072***	0.411	1.035	0.144***	0.195	0.599
	(0.009)			(0.020)			(0.015)			(0.039)		
Log product of land areas in square km	0.007***	1.049	1.723	0.014***	0.948	1.686	0.008***	0.641	1.366	0.030***	1.030	1.749
	(0.001)			(0.002)			(0.001)			(0.005)		
1 for pairs ever in colonial relationship	0.104***	0.267	0.525	0.178***	0.180	0.414	0.148***	0.239	0.514	0.405***	0.215	0.450
	(0.031)			(0.064)			(0.049)			(0.130)		
1 if countries were or are the same country	0.045	0.037	0.254	0.017	0.001	0.047	-0.014	0.002	-0.055	0.213	0.044	0.276
	(0.039)			(0.091)			(0.065)			(0.166)		
Years of coexistence	0.002***	7.803	9.306	0.004***	8.297	9.841	0.003***	8.818	10.303	0.008***	8.336	9.842
	(0.000)			(0.000)			(0.000)			(0.000)		
Major oil producer dummy	0.009**	0.039	0.171	0.020**	0.043	0.179	0.020***	0.081	0.259	0.038**	0.035	0.162
	(0.004)			(0.009)			(0.006)			(0.019)		
Ruggedness (abs. dif.)	0.007*	0.020	-0.032	0.015**	0.033	-0.022	0.010**	0.030	-0.017	0.025	0.023	-0.018
	(0.004)			(0.007)			(0.005)			(0.016)		
Ruggedness (mean)	-0.010*			-0.029***			-0.020***			-0.050**		
	(0.005)			(0.010)			(0.008)			(0.023)		
% tropical area (abs. dif.)	0.000	0.874	1.176	-0.000	1.066	1.363	-0.000	0.794	1.108	-0.000	1.077	1.424
	(0.000)			(0.000)			(0.000)			(0.000)		
% tropical area (mean)	-0.001***			-0.001***			-0.001***			-0.003***		
	(0.000)			(0.000)			(0.000)			(0.000)		
% fertile soil (abs. dif.)	-0.000	0.053	-0.041	0.000	0.086	-0.069	-0.000	0.101	-0.052	0.000	0.060	-0.068
	(0.000)			(0.000)			(0.000)			(0.000)		
% fertile soil (mean)	0.000***			0.001***			0.001***			0.001***		
	(0.000)			(0.000)			(0.000)			(0.000)		
% desert area (abs. dif.)	0.000	0.419	0.121	0.002*	0.507	0.137	0.001*	0.415	0.098	0.002	0.484	0.140
	(0.001)			(0.001)			(0.001)			(0.002)		
% desert area (mean)	-0.003***			-0.008***			-0.005***			-0.013***		
	(0.001)			(0.002)			(0.002)			(0.004)		
Avg. distance to coast (abs. dif.)	0.009	0.152	0.082	0.046	0.295	0.103	0.038*	0.511	0.196	0.037	0.183	0.109
	(0.013)			(0.028)			(0.021)			(0.056)		
Avg. distance to coast (mean)	0.020			0.026			0.034			0.100		
	(0.025)			(0.057)			(0.042)			(0.108)		
% within 100 km. of ice-free coast (abs. dif.)	0.000	0.012	-0.052	-0.000	0.008	-0.035	-0.000	0.018	-0.052	-0.000	0.002	-0.020
	(0.000)			(0.000)			(0.000)			(0.000)		
% within 100 km. of ice-free coast (mean)	0.000			0.000			0.000			0.000		
	(0.000)			(0.000)			(0.000)			(0.001)		
Observations	13033			13033			13033			13033		
R^2	0.250			0.283			0.302			0.252		

Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.5 – Decomposition of the measure E_i into terms $Cov(\beta_i x_i, \beta_j x_j)/Var(y)$ when considering the dependent variable “Ever a conflict”

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	
		Genetic distance (1500)	Log geodesic distance	Log absolute difference in longitudes	Log absolute difference in latitudes	1 for contiguity	Number of landlocked countries in the pair	Number of island countries in the pair	1 if pair shares at least one sea or ocean	Log product of land areas in square km	1 for pairs ever in colonial relationship	1 if countries were or are the same country	Years of coexistence	Major oil producer dummy	Ruggedness	% tropical area	% fertile soil	% desert area	Avg. distance to coast	% within 100 km. of ice-free coast	Ei
1	Genetic distance (1500)	0.001	0.001	0.000	0.000	0.001	0.000	-0.000	0.000	-0.000	0.000	0.000	0.001	0.000	-0.000	0.001	0.000	-0.000	-0.000	0.000	0.00
2	Log geodesic distance	0.001	0.003	0.000	0.001	0.005	-0.000	-0.001	0.001	-0.000	0.000	0.000	0.001	-0.000	-0.000	0.001	-0.000	-0.000	0.000	-0.000	0.01
3	Log absolute difference in longitudes	0.000	0.000	0.000	0.000	0.000	-0.000	-0.000	0.000	-0.000	0.000	0.000	-0.000	-0.000	-0.000	0.000	-0.000	-0.000	0.000	-0.000	0.00
4	Log absolute difference in latitudes	0.000	0.001	0.000	0.002	0.002	0.000	-0.000	0.000	-0.000	-0.000	0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	0.000	0.00
5	1 for contiguity	0.001	0.005	0.000	0.002	0.070	-0.001	-0.002	0.001	0.002	0.001	0.002	0.005	0.000	-0.000	0.001	-0.000	-0.001	0.000	-0.000	0.09
6	Number of landlocked countries in the pair	0.000	-0.000	-0.000	0.000	-0.001	0.004	0.001	0.001	-0.000	0.000	-0.000	0.003	0.000	0.000	-0.001	0.000	0.000	-0.001	0.000	0.00
7	Number of island countries in the pair	-0.000	-0.001	-0.000	-0.000	-0.002	0.001	0.006	0.000	-0.004	-0.000	-0.000	-0.004	-0.000	0.000	-0.002	0.000	0.001	-0.001	0.000	-0.01
8	1 if pair shares at least one sea or ocean	0.000	0.001	0.000	0.000	0.001	0.001	0.000	0.002	-0.000	0.000	0.000	0.001	0.000	-0.000	-0.001	0.000	0.000	-0.000	0.000	0.01
9	Log product of land areas in square km	-0.000	-0.000	-0.000	-0.000	0.002	-0.000	-0.004	-0.000	0.009	0.000	-0.000	0.008	0.001	0.000	0.003	-0.001	-0.001	0.002	-0.000	0.02
10	1 for pairs ever in colonial relationship	0.000	0.000	0.000	-0.000	0.001	0.000	-0.000	0.000	0.000	0.003	0.000	0.001	0.000	0.000	0.000	0.000	0.000	-0.000	0.000	0.01
11	1 if countries were or are the same country	0.000	0.000	0.000	0.000	0.002	-0.000	-0.000	0.000	-0.000	0.000	0.000	0.000	-0.000	-0.000	-0.000	0.000	-0.000	-0.000	-0.000	0.00
12	Years of coexistence	0.001	0.001	-0.000	-0.000	0.005	0.003	-0.004	0.001	0.008	0.001	0.000	0.074	0.001	-0.000	0.003	-0.000	0.001	-0.001	-0.000	0.09
13	Major oil producer dummy	0.000	-0.000	-0.000	-0.000	0.000	0.000	-0.000	0.000	0.001	0.000	-0.000	0.001	0.000	0.000	0.000	-0.000	-0.000	0.000	-0.000	0.00
14	Ruggedness	-0.000	-0.000	-0.000	-0.000	-0.000	0.000	0.000	-0.000	0.000	0.000	-0.000	-0.000	0.000	0.000	-0.000	-0.000	-0.000	0.000	-0.000	-0.00
15	% tropical area	0.001	0.001	0.000	-0.000	0.001	-0.001	-0.002	-0.001	0.003	0.000	-0.000	0.003	0.000	-0.000	0.009	-0.000	-0.002	0.001	-0.000	0.01
16	% fertile soil	0.000	-0.000	-0.000	-0.000	-0.000	0.000	0.000	0.000	-0.001	0.000	0.000	-0.000	-0.000	-0.000	-0.000	0.001	0.001	-0.000	0.000	-0.00
17	% desert area	-0.000	-0.000	-0.000	-0.000	-0.001	0.000	0.001	0.000	-0.001	0.000	-0.000	0.001	-0.000	-0.000	-0.002	0.001	0.004	-0.000	0.000	0.00
18	Avg. distance to coast	-0.000	0.000	0.000	-0.000	0.000	-0.001	-0.001	-0.000	0.002	-0.000	-0.000	-0.001	0.000	0.000	0.001	-0.000	-0.000	0.001	-0.000	0.00
19	% within 100 km. of ice-free coast	0.000	-0.000	-0.000	0.000	-0.000	0.000	0.000	0.000	-0.000	0.000	-0.000	-0.000	-0.000	-0.000	-0.000	0.000	0.000	-0.000	0.000	-0.00

Table A.6 – Correlation matrix

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25
		Genetic distance (1500)	Log geodesic distance	Log absolute difference in longitudes	Log absolute difference in latitudes	1 for contiguity	Number of landlocked countries in the pair	Number of island countries in the pair	1 if pair shares at least one sea or ocean	Log product of land areas in square km	1 for pairs ever in colonial relationship	1 if countries were or are the same country	Years of coexistence	Major oil producer dummy	Ruggedness (abs. dif.)	Ruggedness (mean)	% tropical area (abs. dif.)	% tropical area (mean)	% fertile soil (abs. dif.)	% fertile soil (mean)	% desert area (abs. dif.)	% desert area (mean)	Avg. distance to coast (abs. dif.)	Avg. distance to coast (mean)	% within 100 km. of ice-free coast (abs. dif.)	% within 100 km. of ice-free coast (mean)
1	Genetic distance (1500)	1.00	0.54	0.34	0.22	-0.16	0.04	0.01	-0.13	0.10	-0.02	-0.12	-0.12	-0.04	0.03	-0.01	0.21	0.25	-0.03	-0.01	-0.05	-0.06	0.06	0.07	0.04	-0.10
2	Log geodesic distance	0.54	1.00	0.79	0.42	-0.36	-0.11	0.19	-0.27	0.04	-0.05	-0.26	-0.04	0.04	-0.01	-0.03	0.35	0.26	0.03	0.03	-0.07	-0.08	0.01	-0.07	0.11	0.15
3	Log absolute difference in longitudes	0.34	0.79	1.00	0.10	-0.25	-0.13	0.17	-0.22	0.02	-0.03	-0.19	0.01	0.06	-0.06	-0.07	0.21	0.20	0.01	0.04	-0.05	-0.06	0.05	-0.05	0.11	0.19
4	Log absolute difference in latitudes	0.22	0.42	0.10	1.00	-0.22	0.01	0.02	-0.15	0.08	0.02	-0.16	0.01	0.02	0.02	-0.01	0.37	-0.11	0.03	0.04	-0.06	-0.07	-0.00	0.01	0.01	-0.05
5	1 for contiguity	-0.16	-0.36	-0.25	-0.22	1.00	0.04	-0.09	0.12	0.09	0.08	0.33	0.07	0.01	-0.04	-0.02	-0.10	-0.05	-0.08	-0.03	0.00	0.03	-0.02	0.08	-0.09	-0.10
6	Number of landlocked countries in the pair	0.04	-0.11	-0.13	0.01	0.04	1.00	-0.23	-0.22	0.08	-0.04	0.03	-0.16	-0.21	0.11	0.17	-0.10	-0.23	-0.07	-0.03	0.04	0.05	0.41	0.57	-0.00	-0.54
7	Number of island countries in the pair	0.01	0.19	0.17	0.02	-0.09	-0.23	1.00	0.13	-0.58	-0.02	-0.00	-0.21	-0.12	0.06	0.03	0.11	0.31	0.17	0.21	-0.12	-0.12	-0.13	-0.34	0.16	0.58
8	1 if pair shares at least one sea or ocean	-0.13	-0.27	-0.22	-0.15	0.12	-0.22	0.13	1.00	-0.05	0.06	0.10	0.11	0.08	-0.03	-0.02	-0.06	0.16	-0.04	0.01	-0.04	-0.03	-0.09	-0.13	-0.03	0.19
9	Log product of land areas in square km	0.10	0.04	0.02	0.08	0.09	0.08	-0.58	-0.05	1.00	0.04	-0.01	0.32	0.35	-0.20	-0.17	-0.11	-0.28	-0.17	-0.33	0.21	0.24	0.28	0.53	-0.18	-0.64
10	1 for pairs ever in colonial relationship	-0.02	-0.05	-0.03	0.02	0.08	-0.04	-0.02	0.06	0.04	1.00	0.03	0.05	0.03	-0.02	-0.03	-0.00	-0.06	-0.01	0.03	-0.02	-0.02	-0.02	-0.01	-0.04	0.03
11	1 if countries were or are the same country	-0.12	-0.26	-0.19	-0.16	0.33	0.03	-0.00	0.10	-0.01	0.03	1.00	0.03	-0.04	-0.04	-0.02	-0.05	0.05	-0.03	0.03	0.01	0.02	-0.02	0.01	-0.06	-0.02
12	Years of coexistence	-0.12	-0.04	0.01	0.01	0.07	-0.16	-0.21	0.11	0.32	0.05	0.03	1.00	0.13	-0.04	0.03	-0.07	-0.12	-0.14	-0.05	-0.06	-0.06	-0.07	-0.04	-0.05	-0.04
13	Major oil producer dummy	-0.04	0.04	0.06	0.02	0.01	-0.21	-0.12	0.08	0.35	0.03	-0.04	0.13	1.00	-0.10	-0.12	-0.03	-0.09	0.01	-0.27	0.19	0.21	-0.00	0.06	-0.04	-0.10
14	Ruggedness (abs. dif.)	0.03	-0.01	-0.06	0.02	-0.04	0.11	0.06	-0.03	-0.20	-0.02	-0.04	-0.04	-0.10	1.00	0.62	0.00	0.00	-0.01	0.03	-0.04	-0.04	-0.02	-0.05	0.03	0.04
15	Ruggedness (mean)	-0.01	-0.03	-0.07	-0.01	-0.02	0.17	0.03	-0.02	-0.17	-0.03	-0.02	0.03	-0.12	0.62	1.00	-0.02	-0.07	-0.06	0.04	-0.11	-0.11	-0.04	-0.07	0.03	0.05
16	% tropical area (abs. dif.)	0.21	0.35	0.21	0.37	-0.10	-0.10	0.11	-0.06	-0.11	-0.00	-0.05	-0.07	-0.03	0.00	-0.02	1.00	0.30	0.01	0.06	-0.07	-0.10	-0.06	-0.12	0.10	0.12
17	% tropical area (mean)	0.25	0.26	0.20	-0.11	-0.05	-0.23	0.31	0.16	-0.28	-0.06	0.05	-0.12	-0.09	0.00	-0.07	0.30	1.00	-0.02	0.15	-0.25	-0.27	-0.17	-0.27	0.06	0.31
18	% fertile soil (abs. dif.)	-0.03	0.03	0.01	0.03	-0.08	-0.07	0.17	-0.04	-0.17	-0.01	-0.03	-0.14	0.01	-0.01	-0.06	0.01	-0.02	1.00	0.18	0.13	0.09	0.01	-0.07	0.06	0.10
19	% fertile soil (mean)	-0.01	0.03	0.04	0.04	-0.03	-0.03	0.21	0.01	-0.33	0.03	0.03	-0.05	-0.27	0.03	0.04	0.06	0.15	0.18	1.00	-0.35	-0.38	-0.21	-0.29	0.05	0.23
20	% desert area (abs. dif.)	-0.05	-0.07	-0.05	-0.06	0.00	0.04	-0.12	-0.04	0.21	-0.02	0.01	-0.06	0.19	-0.04	-0.11	-0.07	-0.25	0.13	-0.35	1.00	0.96	0.13	0.19	-0.03	-0.16
21	% desert area (mean)	-0.06	-0.08	-0.06	-0.07	0.03	0.05	-0.12	-0.03	0.24	-0.02	0.02	-0.06	0.21	-0.04	-0.11	-0.10	-0.27	0.09	-0.38	0.96	1.00	0.14	0.21	-0.04	-0.18
22	Avg. distance to coast (abs. dif.)	0.06	0.01	0.05	-0.00	-0.02	0.41	-0.13	-0.09	0.28	-0.02	-0.02	-0.07	-0.00	-0.02	-0.04	-0.06	-0.17	0.01	-0.21	0.13	0.14	1.00	0.80	0.34	-0.34
23	Avg. distance to coast (mean)	0.07	-0.07	-0.05	0.01	0.08	0.57	-0.34	-0.13	0.53	-0.01	0.01	-0.04	0.06	-0.05	-0.07	-0.12	-0.27	-0.07	-0.29	0.19	0.21	0.80	1.00	-0.07	-0.69
24	% within 100 km. of ice-free coast (abs. dif.)	0.04	0.11	0.11	0.01	-0.09	-0.00	0.16	-0.03	-0.18	-0.04	-0.06	-0.05	-0.04	0.03	0.03	0.10	0.06	0.06	0.05	-0.03	-0.04	0.34	-0.07	1.00	0.21
25	% within 100 km. of ice-free coast (mean)	-0.10	0.15	0.19	-0.05	-0.10	-0.54	0.58	0.19	-0.64	0.03	-0.02	-0.04	-0.10	0.04	0.05	0.12	0.31	0.10	0.23	-0.16	-0.18	-0.34	-0.69	0.21	1.00

B.3 Supplementary tables related to Section 5

Table A.7 – Decomposition of the measure E_i into terms $Cov(\beta_i x_i, \beta_j x_j)/Var(y)$

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	
		Malaria	Temperature	Precipitation	Ruggedness	Distance to coast	Soil fertility	Tropical area	Desert area	Latitude	Diamonds	OPEC dummy	Years since neolitic transition	Slave export intensity	Ethnolinguistic fractionalization	European descent	Genetic diversity	WB region dummies	Religion	Legal origin dummies	**Ei**
1	Malaria	7.1%	0.5%	0.8%	-0.5%	0.5%	-0.4%	0.3%	0.0%	-1.2%	-0.1%	0.1%	2.1%	3.0%	-0.4%	2.0%	1.2%	4.6%	0.7%	-1.4%	**19.0%**
2	Temperature	0.5%	0.1%	0.2%	-0.1%	-0.2%	-0.1%	0.1%	0.0%	-0.2%	0.0%	-0.1%	0.1%	0.2%	0.0%	0.3%	0.1%	0.7%	0.1%	-0.3%	**1.4%**
3	Precipitation	0.8%	0.2%	2.0%	0.1%	-1.1%	0.2%	0.3%	0.2%	-0.6%	0.0%	0.2%	0.4%	0.0%	0.0%	0.2%	-0.2%	1.6%	-1.3%	-0.8%	**2.0%**
4	Ruggedness	-0.5%	-0.1%	0.1%	0.9%	-0.1%	0.2%	-0.1%	0.0%	0.1%	0.0%	0.2%	-0.2%	-0.4%	0.1%	0.0%	0.0%	0.0%	-0.1%	0.0%	**0.2%**
5	Distance to coast	0.5%	-0.2%	-1.1%	-0.1%	5.1%	-0.6%	-0.1%	-0.1%	0.1%	0.0%	0.1%	0.2%	0.3%	-0.1%	0.4%	0.2%	-0.2%	0.9%	1.9%	**7.2%**
6	Soil fertility	-0.4%	-0.1%	0.2%	0.2%	-0.6%	0.8%	0.0%	0.1%	0.1%	0.0%	0.3%	0.0%	-0.1%	0.1%	-0.4%	-0.1%	-0.2%	-0.6%	0.4%	**-0.4%**
7	Tropical area	0.3%	0.1%	0.3%	-0.1%	-0.1%	0.0%	0.1%	0.0%	-0.1%	0.0%	0.0%	0.1%	0.1%	0.0%	0.1%	0.0%	0.4%	-0.1%	-0.1%	**1.0%**
8	Desert area	0.0%	0.0%	0.2%	0.0%	-0.1%	0.1%	0.0%	0.1%	0.0%	0.0%	0.1%	0.0%	0.0%	0.0%	-0.1%	0.0%	0.0%	-0.3%	0.0%	**0.0%**
9	Latitude	-1.2%	-0.2%	-0.6%	0.1%	0.1%	0.1%	-0.1%	0.0%	0.5%	0.0%	0.2%	-0.4%	-0.4%	0.1%	-0.5%	-0.4%	-1.3%	0.2%	0.6%	**-3.2%**
10	Diamonds	-0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	0.0%	-0.1%	0.0%	0.0%	0.0%	0.0%	-0.1%	0.0%	0.1%	**-0.2%**
11	OPEC dummy	0.1%	-0.1%	0.2%	0.2%	0.1%	0.3%	0.0%	0.1%	0.2%	0.0%	1.7%	0.1%	-0.1%	0.1%	-0.3%	-0.1%	0.1%	-0.6%	0.3%	**2.0%**
12	Years since neolitic transition	2.1%	0.1%	0.4%	-0.2%	0.2%	0.0%	0.1%	0.0%	-0.4%	-0.1%	0.1%	1.5%	1.0%	-0.1%	0.6%	0.5%	1.9%	-0.4%	-0.9%	**6.5%**
13	Slave export intensity	3.0%	0.2%	0.0%	-0.4%	0.3%	-0.1%	0.1%	0.0%	-0.4%	0.0%	-0.1%	1.0%	2.1%	-0.2%	0.8%	0.6%	2.0%	0.6%	-0.8%	**8.7%**
14	Ethnolinguistic fractionalization	-0.4%	0.0%	0.0%	0.1%	-0.1%	0.1%	0.0%	0.0%	0.1%	0.0%	0.1%	-0.1%	-0.2%	0.1%	-0.1%	-0.1%	-0.4%	-0.1%	0.0%	**-1.2%**
15	European descent	2.0%	0.3%	0.2%	0.0%	0.4%	-0.4%	0.1%	-0.1%	-0.5%	0.0%	-0.3%	0.6%	0.8%	-0.1%	1.8%	0.5%	2.5%	1.4%	-1.0%	**8.1%**
16	Genetic diversity	1.2%	0.1%	-0.2%	0.0%	0.2%	-0.1%	0.0%	0.0%	-0.4%	0.0%	-0.1%	0.5%	0.6%	-0.1%	0.5%	2.1%	1.0%	-0.1%	-0.4%	**5.0%**
17	WB region dummies	4.6%	0.7%	1.6%	0.0%	-0.2%	-0.2%	0.4%	0.0%	-1.3%	-0.1%	0.1%	1.9%	2.0%	-0.4%	2.5%	1.0%	11.4%	0.0%	-3.6%	**20.3%**
18	Religion	0.7%	0.1%	-1.3%	-0.1%	0.9%	-0.6%	-0.1%	-0.3%	0.2%	0.0%	-0.6%	-0.4%	0.6%	-0.1%	1.4%	-0.1%	0.0%	4.6%	0.3%	**5.3%**
19	Legal origin dummies	-1.4%	-0.3%	-0.8%	0.0%	1.9%	0.4%	-0.1%	0.0%	0.6%	0.1%	0.3%	-0.9%	-0.8%	0.0%	-1.0%	-0.4%	-3.6%	0.3%	8.8%	**3.1%**

Table A.8 – Correlation matrix

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32
		Malaria	Temperature	Precipitation	Ruggedness	Distance to coast	Soil fertility	Tropical area	Desert area	Latitude	Diamonds	OPEC dummy	Years since neolitic transition	Slave export intensity	Ethnolinguistic fractionalization	European descent	Genetic diversity	Protestant share	Catholic share	Muslim share	Other religions share	French civil law	Common law legal origin	Socialist law	German civil law	Scandinavian law	Europe and central Asia	East Asia and Pacific	Latin America and Caribbean	Middle East and North Africa	North America	South Asia	Sub-Saharan Africa
1	Malaria	100%	59%	22%	-21%	9%	-17%	51%	1%	-63%	14%	-3%	-65%	76%	53%	-56%	29%	1%	-13%	10%	2%	19%	13%	-27%	-14%	-12%	-47%	3%	-21%	-21%	-8%	-2%	81%
2	Temperature	59%	100%	35%	-33%	-27%	-21%	65%	17%	-67%	11%	22%	-33%	47%	42%	-64%	-4%	-23%	1%	26%	-16%	38%	22%	-51%	-21%	-29%	-74%	5%	24%	16%	-25%	3%	46%
3	Precipitation	22%	35%	100%	4%	-36%	16%	79%	-39%	-54%	6%	-9%	-21%	2%	7%	-11%	-49%	4%	33%	-41%	8%	7%	11%	-20%	5%	-7%	-29%	33%	40%	-42%	-7%	6%	4%
4	Ruggedness	-21%	-33%	4%	100%	-3%	20%	-23%	-18%	21%	-11%	-14%	13%	-30%	-24%	-3%	-6%	-8%	-1%	-7%	14%	-10%	-2%	9%	19%	-5%	13%	3%	-3%	-5%	-3%	23%	-18%
5	Distance to coast	9%	-27%	-36%	-3%	100%	-32%	-20%	22%	5%	4%	-5%	-6%	9%	23%	-14%	13%	-6%	-17%	17%	3%	-11%	-8%	29%	-8%	-8%	7%	-7%	-17%	-13%	19%	4%	13%
6	Soil fertility	-17%	-21%	16%	20%	-32%	100%	1%	-41%	22%	-16%	-27%	1%	-5%	-25%	39%	-5%	-5%	23%	-34%	17%	-7%	-9%	19%	9%	-13%	27%	-5%	5%	-25%	-4%	4%	-11%
7	Tropical area	51%	65%	79%	-23%	-20%	1%	100%	-25%	-75%	5%	0%	-38%	34%	34%	-38%	-27%	-4%	25%	-21%	-2%	24%	11%	-30%	-15%	-13%	-51%	15%	40%	-29%	-9%	-2%	34%
8	Desert area	1%	17%	-39%	-18%	22%	-41%	-25%	100%	7%	-3%	25%	6%	5%	8%	-22%	11%	-13%	-24%	50%	-23%	6%	1%	-3%	-6%	-5%	-10%	-8%	-12%	32%	-4%	-2%	3%
9	Latitude	-63%	-67%	-54%	21%	5%	22%	-75%	7%	100%	-8%	-17%	41%	-42%	-48%	52%	3%	7%	-15%	5%	6%	-26%	-18%	38%	15%	19%	58%	-11%	-17%	15%	12%	4%	-52%
10	Diamonds	14%	11%	6%	-11%	4%	-16%	5%	-3%	-8%	100%	-3%	-32%	13%	13%	-13%	9%	14%	-9%	-7%	10%	-14%	27%	-10%	-4%	-3%	-13%	-5%	-8%	-7%	-2%	-4%	30%
11	OPEC dummy	-3%	22%	-9%	-14%	-5%	-27%	0%	25%	-17%	-3%	100%	4%	6%	20%	-20%	2%	-10%	-5%	31%	-24%	21%	-4%	-16%	-6%	-5%	-20%	-3%	-1%	45%	-4%	-7%	-5%
12	Years since neolitic transition	-65%	-33%	-21%	13%	-6%	1%	-38%	6%	41%	-32%	4%	100%	-58%	-33%	34%	-17%	-31%	-3%	17%	2%	-7%	-20%	28%	6%	-1%	37%	8%	4%	33%	6%	15%	-77%
13	Slave export intensity	76%	47%	2%	-30%	9%	-5%	34%	5%	-42%	13%	6%	-58%	100%	60%	-40%	36%	-1%	-16%	16%	0%	20%	8%	-27%	-10%	-8%	-33%	-17%	-22%	-14%	-6%	-11%	79%
14	Ethnolinguistic fractionalization	53%	42%	7%	-24%	23%	-25%	34%	8%	-48%	13%	20%	-33%	60%	100%	-43%	17%	-8%	-15%	21%	-2%	14%	17%	-17%	-21%	-24%	-39%	-18%	-2%	-5%	6%	5%	52%
15	European descent	-56%	-64%	-11%	-3%	-14%	39%	-38%	-22%	52%	-13%	-20%	34%	-40%	-43%	100%	-8%	21%	39%	-46%	-3%	-15%	-27%	33%	11%	26%	70%	-17%	10%	-22%	13%	-17%	-47%
16	Genetic diversity	29%	-4%	-49%	-6%	13%	-5%	-27%	11%	3%	9%	2%	-17%	36%	17%	-8%	100%	9%	-38%	28%	5%	-8%	8%	4%	-8%	1%	16%	-42%	-57%	21%	-2%	-7%	46%
17	Protestant share	1%	-23%	4%	-8%	-6%	-5%	-4%	-13%	7%	14%	-10%	-31%	-1%	-8%	21%	9%	100%	-8%	-33%	-13%	-27%	18%	-18%	11%	66%	12%	-2%	-9%	-20%	15%	-12%	11%
18	Catholic share	-13%	1%	33%	-1%	-17%	23%	25%	-24%	-15%	-9%	-5%	-3%	-16%	-15%	39%	-38%	-8%	100%	-53%	-46%	40%	-24%	-18%	3%	-14%	1%	-17%	58%	-23%	3%	-18%	-13%
19	Muslim share	10%	26%	-41%	-7%	17%	-34%	-21%	50%	5%	-7%	31%	17%	16%	21%	-46%	28%	-33%	-53%	100%	-36%	17%	-1%	-9%	-13%	-11%	-16%	-15%	-29%	56%	-8%	11%	7%
20	Other religions share	2%	-16%	8%	14%	3%	17%	-2%	-23%	6%	10%	-24%	2%	0%	-2%	-3%	5%	-13%	-46%	-36%	100%	-47%	18%	41%	5%	-12%	10%	37%	-26%	-27%	-3%	14%	0%
21	French civil law	19%	38%	7%	-10%	-11%	-7%	24%	6%	-26%	-14%	21%	-7%	20%	14%	-15%	-8%	-27%	40%	17%	-47%	100%	-57%	-47%	-17%	-15%	-33%	-21%	29%	23%	-11%	-14%	17%
22	Common law legal origin	13%	22%	11%	-2%	-8%	-9%	11%	1%	-18%	27%	-4%	-20%	8%	17%	-27%	8%	18%	-24%	-1%	18%	-57%	100%	-32%	-11%	-10%	-30%	9%	-11%	-4%	18%	28%	19%
23	Socialist law	-27%	-51%	-20%	9%	29%	19%	-30%	-3%	38%	-10%	-16%	28%	-27%	-17%	33%	4%	-18%	-18%	-9%	41%	-47%	-32%	100%	-9%	-8%	59%	10%	-17%	-18%	-6%	-11%	-32%
24	German civil law	-14%	-21%	5%	19%	-8%	9%	-15%	-6%	15%	-4%	-6%	6%	-10%	-21%	11%	-8%	11%	3%	-13%	5%	-17%	-11%	-9%	100%	-3%	12%	19%	-8%	-7%	-2%	-4%	-11%
25	Scandinavian law	-12%	-29%	-7%	-5%	-8%	-13%	-13%	-5%	19%	-3%	-5%	-1%	-8%	-24%	26%	1%	66%	-14%	-11%	-12%	-15%	-10%	-8%	-3%	100%	25%	-5%	-7%	-6%	-2%	-4%	-10%
26	Europe and central Asia	-47%	-74%	-29%	13%	7%	27%	-51%	-10%	58%	-13%	-20%	37%	-33%	-39%	70%	16%	12%	1%	-16%	10%	-33%	-30%	59%	12%	25%	100%	-21%	-27%	-23%	-7%	-14%	-40%
27	East Asia and Pacific	3%	5%	33%	3%	-7%	-5%	15%	-8%	-11%	-5%	-3%	8%	-17%	-18%	-17%	-42%	-2%	-17%	-15%	37%	-21%	9%	10%	19%	-5%	-21%	100%	-14%	-12%	-4%	-7%	-21%
28	Latin America and Caribbean	-21%	24%	40%	-3%	-17%	5%	40%	-12%	-17%	-8%	-1%	4%	-22%	-2%	10%	-57%	-9%	58%	-29%	-26%	29%	-11%	-17%	-8%	-7%	-27%	-14%	100%	-16%	-5%	-9%	-27%
29	Middle East and North Africa	-21%	16%	-42%	-5%	-13%	-25%	-29%	32%	15%	-7%	45%	33%	-14%	-5%	-22%	21%	-20%	-23%	56%	-27%	23%	-4%	-18%	-7%	-6%	-23%	-12%	-16%	100%	-4%	-8%	-23%
30	North America	-8%	-25%	-7%	-3%	19%	-4%	-9%	-4%	12%	-2%	-4%	6%	-6%	6%	13%	-2%	15%	3%	-8%	-3%	-11%	18%	-6%	-2%	-2%	-7%	-4%	-5%	-4%	100%	-2%	-7%
31	South Asia	-2%	3%	6%	23%	4%	4%	-2%	-2%	4%	-4%	-7%	15%	-11%	5%	-17%	-7%	-12%	-18%	11%	14%	-14%	28%	-11%	-4%	-4%	-14%	-7%	-9%	-8%	-2%	100%	-14%
32	Sub-Saharan Africa	81%	46%	4%	-18%	13%	-11%	34%	3%	-52%	30%	-5%	-77%	79%	52%	-47%	46%	11%	-13%	7%	0%	17%	19%	-32%	-11%	-10%	-40%	-21%	-27%	-23%	-7%	-14%	100%

C Appendix related to Section 4

C.1 Data sources

The following variables are taken from the dataset of Nunn and Puga (2012): the measure of terrain ruggedness, the average distance to the nearest ice-free coast, the indicator of diamonds extraction, the percentage of each country with fertile soil, the percentage of tropical land, the percentage of desert land,the measure of slave export intensity, and the percentage of the population of European descent.

The following variables are taken from the dataset of Ashraf and Galor (2013): the percentage of the population at risk of malaria, the measure of genetic diversity of Ashraf and Galor (2013) and its square, the religion shares, the number of years since a country transitioned from hunting and gathering to agriculture adjusted for population ancestry (log), and the OPEC dummy. For Lithuania and Eritrea, data on religion shares was taken from the Pew-Tempelton project on "Global Religious Futures". For Equatorial Guinea, Eritrea, and Comoros, the number of years since the neolithic transition was estimated as the average in neighboring countries (Cameroon and Gabon for Equatorial Guinea, Ethiopia and Sudan for Eritrea, and Madagascar for Comoros). The percentage of the population at risk of malaria is assumed to be equal to 0 in Bahrain (as in neighboring Qatar), equal to 0 in Malta (as in neighboring Italy), and equal to 1 in Comoros (as in neighboring Madagascar). Similar results are obtained without these adjustments.

The following variables are taken from the dataset of Alesina et al. (2015): the log of real GDP per person in 2000, the absolute latitude of countries, the average annual temperatures in Kelvin degrees, the average annual precipitation in mm, the legal origin dummies, and the measure of ethnolinguistic fragmentation.

The regional dummies are based on the World Bank classification.