ERASMUS UNIVERSITY ROTTERDAM

BACHELOR THESIS

ECONOMETRICS AND OPERATIONAL RESEARCH

The Empirical Validation of Double/Debiased Machine Learning

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July 15, 2018

ABSTRACT

In this paper, a complementary method to classical statistical modeling such as ordinary least squares, and instrumental variables estimation, is introduced. This method, double/debiased machine learning, is applied in the presence of a high-dimensional nuisance parameter set, which possibly interferes with the estimator for the treatment effect. The following techniques are introduced and thoroughly examined: lasso, random forests, neural nets, boosted trees, and an ensemble method. Thereafter, estimates obtained by these techniques are compared to those obtained by traditional OLS and IV estimation. Specifically, research results obtained from Nunn and Wantchekon (2011) and Acemoglu et al. (2005) are used to empirically examine this nonparametric estimation. The hypothesis that DML performs better out-of-sample estimations is supported by Nunn and Wantchekon (2011), which therefore questions the reliability of classical statistical modeling. This hypothesis can not be confirmed nor refuted by Acemoglu et al. (2005).

1 Introduction and Relevance

As knowledge about the theory behind machine learning (ML) expands, its applications become increasingly present in daily life. Not only has ML been introduced in search ranking, for instance by transforming Google Search (Metz, 2016), but also are ML algorithms used for advertisement targeting (Recchia, 2018) and for personal feeds like Facebook's (Oremus, 2016).

Before attempting to validly use machine learning, one has to define this type of statistical modeling. Murphy (2013) defines Machine Learning as "a set of methods that can automatically detect patterns in data, and then use the uncovered patterns to predict future data, or to perform other kinds of decision making under uncertainty (such as planning how to collect more data!)". In short, machine learning learns from data profoundly and excels at out-of-sample prediction.

Machine learning possesses multiple advantages over classical statistical modeling. One is that ML can learn from data, instead of using explicitly programmed instructions (Srivastava, 2015). Furthermore, statistical modeling requires a number of assumptions, such as homoskedasticity, independence of observations and a deterministic function, whereas ML requires fewer assumptions. For instance, when estimating for causal interference, econometricians often use local linear regression, which can be used well in practice in a low-dimensional nuisance parameter framework. When more covariates are introduced, however, this method performs worse (Breheny). ML excels at determining which dimensions are relevant, thus reducing the heterogeneity of the used model. In other words, when lots of covariates are introduced, or as Imbens (2015) state, when the regressors vector is of dimension bigger than approximately three, OLS is not admissible, making ML (or semi-/non parametric) methods better suited (Imbens, 2015). Lastly, ML performs well with wide (high number of attributes) and deep (high number of observations) data (Srivastava, 2015). Statistical modeling, however, is often applied to small data with less attributes, otherwise overfitting may occur.

This paper aims to present an alternative, more sophisticated method with regard to well-known estimation techniques. This aim is based on the hypothesis that double/debiased machine learning techniques perform well in estimating a low-dimensional treatment parameter in a framework of high-dimensional nuisance parameters. To demonstrate this use, I apply double/debiased ML techniques to Nunn and Wantchekon (2011), in which a large number of regressors are introduced and regressions are estimated using OLS, and examine whether significantly different results are obtained. The same procedure will be applied to a second paper, namely Acemoglu et al. (2005), in which four covariates are introduced. In order to apply double/debiased machine learning on aforementioned two papers, I will make extensive use of the theory provided in Chernozhukov et al. (2017). The first two papers are social economic papers, that make use of several covariates. I have chosen these paper because not only do they contribute to social scientific research, which allows my paper to have real impact if Nunn and Wantchekon (2011) and Acemoglu et al. (2005)'s results are disputed, but also because these papers are well-fit to apply DML to. As DML accounts for non-linearity in high-dimensional nuisance parameters (Layman, 2015), the unconfoundedness assumption, which will be explained in detail in section 2.3.1, is more likely to hold in comparison with OLS and IV estimation, which regression models are bound to explicitly programmed functions.

This paper mainly contributes to prior findings on the topic of the semi-parametric problem of inference on a low dimensional parameter θ_0, described in this paper as the treatment effect, in the presence of high-dimensional nuisance parameters η_0, by empirically validating the proper use of these debiased/double machine learning techniques on two socially applicable papers. This paper's findings do not necessarily contribute to theoretical scientific research, but rather to empirical studies, that make use of a high-dimensional covariates vector. It argues the reliability of results obtained by OLS and IV regression in the face of DML estimation.

In this paper, I find that the application of DML techniques to the social economic framework of Nunn and Wantchekon (2011) provides significantly different results, thus the hypothesis that DML techniques are well-suited for estimating treatment effects, particularly in a high-dimensional nuisance parameter framework, is supported. Therefore, the conclusions drawn by classical economic estimation techniques, such as OLS and IV, are refuted. Applying DML to Acemoglu et al. (2005), however, does not yield significantly different results from classical statistical regressions. This can be explained by a setting of lower-dimensional nuisance parameters and/or a dataset containing fewer observations, since theoretically DML performs best for high-dimensional nuisance parameters and a big dataset.

The structure of this paper is as follows: the existing literature about the topics of slave trade, European economic and political growth, and double/debiased machine learning will be reviewed (2). Thereafter, the applied methods in these three papers will be depicted and thoroughly explained (3), after which (adjustment of the used) data and code is explained (4). Lastly, the obtained results will be depicted and extensively elaborated on (5). Lastly, this paper will be concluded (6), followed by a profound appendix containing result tables and used code.

2 Existing Literature

2.1 Slave Trade

Throughout its history, Africa has gone through multiple forms of slave trade. Various slave trade routes were established already during the Middle Ages, but most notable were the four main routes between 1400 and 1900: the transatlantic, Read Sea, Indian Ocean, and trans-Saharan routes. During this period, an estimated number ranging from 10 million to 28 million slaves were shipped to the Americas (BBCNews, 2001). Understandably, African slave trade rooted deep into every day life of those affected. It caused an environment of widespread insecurity, which in part made African individuals turn against one another and participate in tricking, kidnapping, and selling each other into slavery (Foundation, 2018). Consequently, this caused shifting relationships not only among family and friends, who could trick each other into slavery, but also between citizens and their local leaders. As chiefs were either willing or forced to cooperate in the capture of slaves, often were men changed for goods by these leaders, which pressurized this relationship.

Enslavement was conducted in various ways, for instance by being sold into slavery by acquaintances, family, and friends. The most commonly used manner, as researched by Koelle (1854) for a sample of 144 slaves living in Freetown, Sierra Leone, was kidnapping. Also capturing during wars and, surprisingly, being sold by friends and relatives have a substantial share of respectively 20 and 25 percent. Lastly, enslavement through the judicial system occurred. Individuals were convicted of crimes such as adultery, theft, witchcraft or murder, and therefore sentenced to slavery (Lovejoy, 2000).

As Nunn and Wantchekon (2011) applies not only to historical slave trade, but also to nowadays trust levels amongst Africans, delving into prior research about cultural characteristics is of high importance. Culture can be viewed as rules-of-thumb for decision-making employed in complex or uncertain environments. Boyd and Richerson (1995) and Boyd and Richerson (2005) point out that it may be optimal for people to develop heuristics in decision-making when retrieving information is costly or imperfect. Slave trade may have affected these heuristics for decision-making by increasing mistrust. Persistence of this shifted trust can be explained from models developed by Guiso et al. (2007) and Tabellini (2008). They show arising equilibria in cultural outcomes, which can be permanently moved in the long-run. These movements, for instance to equilibria of high levels of mistrust, may explain the persistence of mistrust among lineages most affected by the slave trade.

Moreover, this persistence can be explained by complementaries between cultural norms and domestic institutions. Tabellini (2008)'s model suggests that individuals inhibit norms of cooperation from their parents and determine the quality of institutions by making political choices. In this fashion, the equilibrium quality of domestic institutions will be affected through norms of cooperation. This generates a self-enforcing mechanism where a negative shock in cooperation norms causes the future generation not only to be to be less trusting, but also to choose institutions with weaker enforcement.

In their paper, Nunn and Wantchekon (2011) exhibit that differences in trust levels amongst Africans nowadays can be traced back to the Indian Ocean and transatlantic slave trades. Particularly, they show that Africans whose ancestors were heavily raided during the slave trade are less trusting today. They exhibit that this relationship is causal and that most impact is through factors internal to the individual, like cultural norms, beliefs and values.

They hypothesize that in areas intensely raided by slave trade, norms of trust towards others were likely less advantage than norms of mistrust, and thus they would have become more prevalent after a while. Nunn and Wantchekon (2011) exhibit that individuals belonging to those ethnic groups that were most exposed to the slave trade show lower levels of trust in their relatives, coethnics, neighbors, and local government today. Their research suggests that the channel internal to the individual accounts for at least half of the reduced-form effect of the slave trade on trust.

2.2 The Rise of Europe

Aforementioned slave trade affected not only those subjected to it in Africa, but also those who imposed it. This slave trade, associated colonialism and other Atlantic trade have played a big role in Western Europe's development between 1500 and 1850, not only economically, but also institutionally. This rising trend could be described as "The First Great Divergence" and is, for instance, stated by Allen (2001) as follows: "It is shown that the divergence in real incomes observed in the mid-nineteenth century was produced between 1500 and 1750 as incomes fell in most European cities but were maintained (not increased) in the economic leaders."

The possible relationship between European countries that were involved in Atlantic trade and their economic and institutional growth after 1500 is described in Acemoglu et al. (2005). This relationship is supported by figure 1, which shows the development in societies that were involved in Atlantic trade in contrast to those that were not.

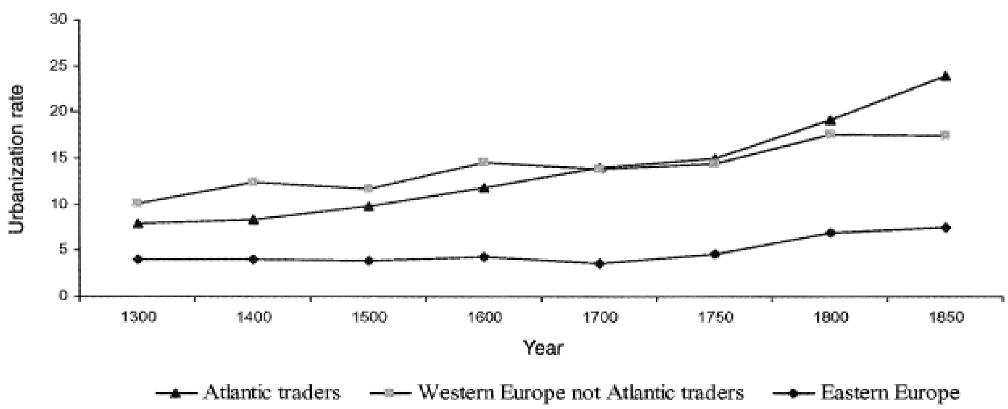

Figure 1: Difference in urbanization rate, weighted by population, between 1300 and 1850 of Atlantic traders, West-European countries not being Atlantic traders, and Eastern Europe. (Figure from Acemoglu et al. (2005))

Acemoglu et al. (2005) hypothesize that Atlantic trade, which is described as the opening of sea routes to Asia, the New World, and Africa and establishing colonial empires, contributed to the growth of Western Europe between 1500 and 1850, not just through direct economic effects, but also indirectly by generating fundamental institutional change. Moreover, their hypothesis suggests that the inclination for institutional change should have been much stronger in those societies that had existing controls on royal power than in those with absolutist governments and trade monopolies controlled by its monarchies, for in these societies Atlantic trade did not derange the status quo. In other words, Acemoglu et al. (2005) hypothesis can be split into 4 subhypotheses:

1. Political institutions limiting and constraining state power are crucial for the incentives to invest and for sustained economic growth;
2. In early modern Europe, such political institutions were supported by commercial interests outside the royal circle, but not welcomed by the monarchy and its allies;
3. Institutions that were favored by politically and economically powerful groups are more likely to prevail;

4. In countries without absolutist political institutions, Atlantic trade and colonialism strengthened commercial interest of groups independent from the monarchy.

As stressed by Acemoglu et al. (2005), they do not intend to offer a mono-causal explanation for the rise of Western Europe, they show however the major role that Atlantic trade played in the "First Great Divergence". This role is also endorsed by Broadberry and Gupta (2006), who state that silver wages in north-western Europe were high compared to the advanced parts of India and China as they reflect high productivity in the trade sector.

2.3 Double/Debiased Machine Learning

On the subject of double/debiased machine learning, research has been conducted on inference based on lasso-type methods for estimating nuisance parameters. Nonetheless, not much about the theory and applications of other double/debiased machine learning methods in a high-dimensional setting has been conducted.

Chernozhukov et al. (2017) builds upon the theory of semi-parametric estimation, such as the kernel spaces of van der Vaart (1996), which focuses on traditional non-parametric methods for estimating θ_0. In their paper, they apply double/debiased machine learning (DML) techniques on a partially linear regression model, with a low-dimensional parameter θ_0 in a framework of high-dimensional nuisance parameters η_0. The following PLR model is considered as a lead example:

$$Y = D\theta_0 + g_0(X) + U, \qquad E[U|X, D] = 0 \tag{1}$$

$$D = m_0(X) + V, \qquad E[V|X] = 0 \tag{2}$$

where Y is the outcome variable, D is the policy/treatment variable of interest, vector $X = [X_1,...,X_p]$ consists of other controls, and U and V are disturbances. Equation 1 is the main equation, and θ_0 is the main regression coefficient that they would like to estimate. Important to note is that nuisance parameters g_0 and m_0 can take on high-dimensional, non-linear functions, which differs substantially from linear regressions such as OLS and IV estimation.

2.3.1 Unconfoundedness

One important aspect double/debiased machine learning should conform to is the assumption of unconfoundedness. Confoundedness may appear when not all relevant variables are taken into account, which occurs often in social sciences (in Social Science, 2015). Consequently, there may exist unobserved confounding variables that influence the dependent variable Y through the treatment variable D. The unconfoundedness assumption describes that any correlation between treatment variable and outcome variable, once controlled for confounding covariates, is actual causal. In more mathematical terms, this means that the dependent variable Y should be orthogonal to the treatment variable D given the covariates capturing variable X. In other words, the treatment variable is practically randomly assigned (once controlled for confounding variables) (Layman, 2015).

To keep track of confounding, equation 2 is introduced. As DML allows for non-linear nuisance parameters and covariate interactions, the assumption of unconfoundedness is more likely to hold compared to OLS and IV regression. Mathematically, this is shown in equation 2 in which the parameter space of nuisance parameters m_0 may be complex, thus allowing for m_0 to take on non-linear functions. This complex parameter space surpasses prior work done in the field of interaction between treatment effect variables and nuisance parameter. Research conducted prior to Chernozhukov et al. (2017) "naively" estimated θ_0 by splitting sample size N in two equal parts: a main part and an auxiliary part. They obtain $\hat{g_0}$ using the auxilary sample and an estimate for θ_0 using the main sample:

$$\hat{\theta_0} = (\frac{1}{n}\sum_{i\in I} D_i^2)^{-1}\frac{1}{n}\sum_{i\in I} D_i(Y_i - \hat{g_0}(X_i)). \tag{3}$$

Although this "naive" estimation yielded mostly effective predictions, it leaves room for misleading estimation of θ_0 due to two substantial biases: *regularization bias* and *bias induced by overfitting*.

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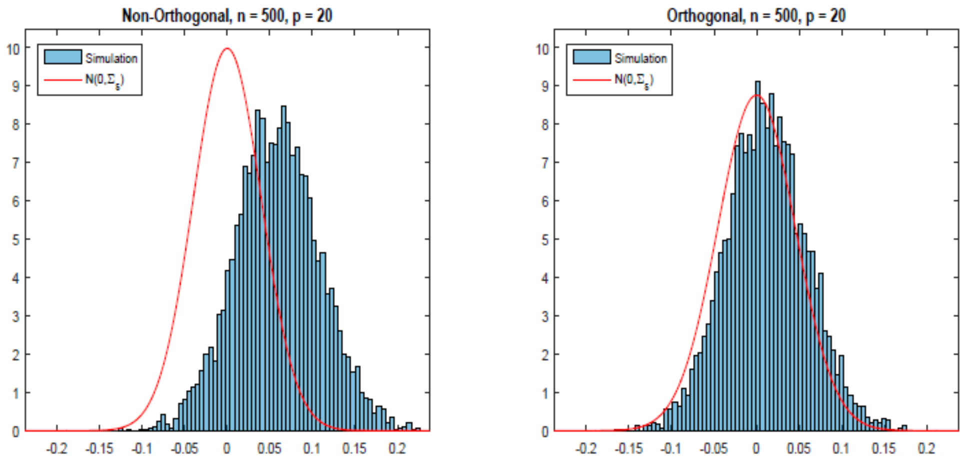

Figure 1. Left Panel: Behavior of a conventional (non-orthogonal) ML estimator, $\widehat{\theta}_0$, in the partially linear model in a simple simulation experiment where we learn g_0 using a random forest. The g_0 in this experiment is a very smooth function of a small number of variables, so the experiment is seemingly favorable to the use of random forests a priori. The histogram shows the simulated distribution of the centered estimator, $\widehat{\theta}_0 - \theta_0$. The estimator is badly biased, shifted much to the right relative to the true value θ_0. The distribution of the estimator (approximated by the blue histogram) is substantively different from a normal approximation (shown by the red curve) derived under the assumption that the bias is negligible. **Right Panel:** Behavior of the orthogonal, DML estimator, $\check{\theta}_0$, in the partially linear model in a simple experiment where we learn nuisance functions using random forests. Note that the simulated data are exactly the same as those underlying left panel. The simulated distribution of the centered estimator, $\check{\theta}_0 - \theta_0$, (given by the blue histogram) illustrates that the estimator is approximately unbiased, concentrates around θ_0, and is well-approximated by the normal approximation obtained in Section 3 (shown by the red curve).

Figure 2: Illustrating the regularization bias when "naively" estimating using Machine Learning. This bias is overcome by orthogonalization.

DML 7

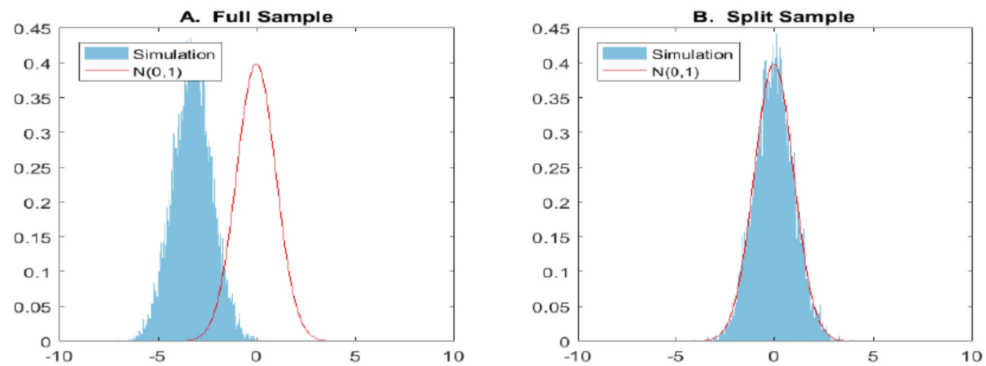

Figure 2. This figure illustrates how the bias resulting from overfitting in the estimation of nuisance functions can cause the main estimator $\check{\theta}_0$ to be biased and how sample splitting completely eliminates this problem. **Left Panel:** The histogram shows the finite-sample distribution of $\check{\theta}_0$ in the partially linear model where nuisance parameters are estimated with overfitting using the full sample, i.e. without sample splitting. The finite-sample distribution is clearly shifted to the left of the true parameter value demonstrating the substantial bias. **Right Panel:** The histogram shows the finite-sample distribution of $\check{\theta}_0$ in the partially linear model where nuisance parameters are estimated with overfitting using the cross-fitting sample-splitting estimator. Here, we see that the use of sample-splitting has completely eliminated the bias induced by overfitting.

Figure 3: Illustrating the bias induced by overfitting when "naively" estimating using Machine Learning

2.3.2 OVERCOMING BIASES

Regularization bias occurs as the estimator for θ_0 in equation 3 has a rate of convergence which is slower than $1/\sqrt{n}$, namely $|\sqrt{n}(\hat{\theta}_0 - \theta_0)| \rightarrow_P \infty$. Particularly, the "naive" estimator of θ_0 fails to be$\sqrt{N}$ consistent.

Overcoming this regularization bias is done by orthogonalization. Specifically by introducing the orthogonal regressor $V = D - m_0(X)$ and obtaining an estimate $\hat{V} = D - \hat{m}_0(X)$, where $\hat{m}_0$ is an ML estimator of m_0 obtained using the auxiliary observations sample. By approximately orthogonalizing D with respect to X and approximately removing the direct effect of confounding by subtracting an estimate of g_0, $\hat{\theta}_0$ removes the effect of regularization bias.

The scaled estimation error of $\hat{\theta}_0$ can be decomposed as follows:

$$\sqrt{n}(\hat{\theta}_0 - \theta_0) = a^* + b^* + c^* \tag{4}$$

Specifically, a^* and b^* possess such properties that they vanish under a broad range of data-generating processes. Besides, the first two terms satisfy:

$$a^* = (EV^2)^{-1}\frac{1}{\sqrt{n}}\sum_{i\in I} V_i U_i \qquad N(0, \sum) \tag{5}$$

$$b^* = (EV^2)^{-1}\frac{1}{\sqrt{n}}\sum_{i\in I}(\hat{m}_0(X_i) - m_0(X_i))(\hat{g}_0(X_i) - g_0(X_i)) \tag{6}$$

The third term c^* contains terms like:

$$\frac{1}{\sqrt{n}}\sum_{i\in I} V_i(\hat{g}_0(X_i) - g_0(X_i)) \tag{7}$$

Veryfing that $\hat{\theta}_0$ has good properties requires the remainder term c^* to be sufficiently well-behaved. Sample splitting plays a key role in guaranteeing that c^* vanishes in probability under weak conditions. This is proven by Chebyshev's inequality, which verifies that term 7 has mean zero and variance which behaves as follows, where $\hat{g}_0$ is estimated using only auxiliary sample observations:

$$\frac{1}{\sqrt{n}}\sum_{i\in I}(\hat{g}_0(X_i)-g_0(X_i))^2 \rightarrow_P 0 \tag{8}$$

This method of sample splitting or "k-cross validation", however, causes the estimator of the parameter of interest to possibly lose a substantial amount of efficiency, for the estimator only uses a subset of the available data, namely the main sample. This efficiency loss is solved by switching the role of the main and auxiliary samples to obtain a second version of the estimator and then averaging the results. This procedure is commonly known as *cross-fitting*. In short, by splitting the sample, cross-fitting prohibits c^* from exploding, and thus removes bias induced by overfitting.

3 Methodology

3.1 Slave Trade

In order to estimate the relationship between the number of slaves that were taken from an individual's ethnic group and the individual's current level of trust, the following baseline equation is estimated by Nunn and Wantchekon (2011):

$$\text{trust}_{i,e,d,c} = \alpha_c + \beta\text{slave exports}_e + \mathbf{X}'_{i,e,d,c}\Gamma + \mathbf{X}'_{d,c}\Omega + \mathbf{X}'_e\Phi + \varepsilon_{i,e,d,c}, \tag{9}$$

where i describes individuals, e ethnic groups, d districts, and c countries. The $\text{trust}_{i,e,d,c}$ variable illustrates one of their five measures of trust, which differ across individuals. The following measures of trust are captured in this variable: *trust of relatives*, *trust of neighbors*, *trust of local council*, *intragroup trust*,and *intergroup trust*. When estimating the relationship between trust amongst Africans today and the slave trade conducted throughout history in Africa, only one of these measures is considered per esimation. Moreover, α_c describes country fixed effects. The variable slave exports_e is a measure of the number of slaves taken from ethnic group e during the slave trade. This variable can take on the following forms of measurement: *slave exports (thousands)*, *exports/area*, *exports/historical pop*, *ln(1+exports)*, *ln(1+exports/area)*, and *ln(1+exports/historical pop)*. β denotes the coefficient of interest: the relationship between the slave exports of an individual's ethnic group and the individual's current trust-level. To estimate these coefficients, Nunn and Wantchekon (2011) makes use of OLS and IV regressions.

Moreover, the vector $\mathbf{X}'_{i,e,d,c}$ describes a number of individual-level covariates, which include the respondent's age, age squared, an indicator variable for gender, a second indicator variable that equals one if the respondent lives in an urban location, five fixed effects for the respondent's living conditions, 18 religion fixed effects, 25 occupation fixed effects, and 10 fixed effects for the educational attainment of the respondent.

Lastly, the vector $\mathbf{X}'_e$ consists of variables capturing the historical characteristics of ethnicities, as well as the differing impacts of colonial rule on separate ethnic groups.

In this paper, I apply double/debiased machine learning techniques to the PLR model as in 2 to replicate Nunn and Wantchekon (2011). This causes the parameter of interest θ_0 to change to β and D to change to slave exports_e. Important to note is that in Section 5 of Chernozhukov et al. (2017) a binary treatment variable is used, while our intended treatment variable takes on continuous values. This, however, is not an issue, since the provided code by Chernozhukov et al. (2017)[1] is able to accept non-binary input for the treatment variable.

Moreover, the elements of vector X become $\alpha, \mathbf{X}'_{i,e,d,c}, \mathbf{X}'_{d,c}$ and $\mathbf{X}'_e$, making functions $g_0(X)$ and $m_0(X)$ describe these elements. Furthermore, Y defines the variable $\text{trust}_{i,e,d,c}$ and U describes $\varepsilon_{i,e,d,c}$, the error term used in the original paper of Nunn and Wantchekon (2011).

[1] For provided code see: https://github.com/VC2015/DMLonGitHub

To investigate whether the possible relationship between slave exports and trust-levels is causal, Nunn and Wantchekon (2011) pursue three strategies. First, they control for additional covariates, such as initial conditions and colonial rule, that possibly are correlated with the slave trade. Consequently, they ensure that the found relationship between dependent variable and treatment variable is caused solely by the treatment variable (or unobservables). Second, they asses the likelihood that our estimates are caused partly due to unobserved heterogeneity across ethnic groups. The last strategy to look for causality involves the historical distance from the coast of an individual's ethnic group as an instrument for slave exports. Furthermore, they distinguish between two channels of causality, internal versus external to the individual, and examine which has the bigger influence.

In this paper, DML is applied to the following tables of Nunn and Wantchekon (2011): Table 1, 2 and 5. These tables make use of a specialization of the main regression stated in this subsection 9. All tables make use of, at least, the following baseline controls: controlling for individual traits, district characteristics and country fixed effects. Specifically this comes down to using controls *age*, *age*^{2}, *a gender dummy*, *an urban dummy*, and different levels of: *education*, *occupation*, *religion*, *living conditions*, and *isocode*. To capture these different levels, multiple dummy variables were created.

Moreover, accounting for an individual's district situation is done by making use of the following district controls: *fractionalization of ethnicity per district* and *proportion of ethnicity per district*

Additionally, some tables in Nunn and Wantchekon (2011) are constructed by controlling for local colonial influence. The variables are captured by colonial controls are considered: *total mission area*, *railway contact*, *malaria*, *explorer contact*, *cities1400dummies*, *v30*, *v33*, and log(*initial population density*), where variable v30 captures precolonial settlement patterns of ethnicity, and v33 precolonial jurisdictional hierarchy beyond the local community. Lastly, colonial population density may serve as a control variable.

To clarify the estimations conducted in Nunn and Wantchekon (2011), the estimated equations in one table (Table 2) are stated below. The other estimated relationships are clarified in the Results section.

Table 2 of Nunn and Wantchekon (2011) shows the relationship between the baseline measure of slave exports, $ln(1+exports/area)$, and different measures of trust. The following controls are taken into account: individual controls, district controls, and country fixed effects. The general linear regression that is considered is as follows:

$$\text{trust}_{i,e,d,c} = \alpha_c + \beta \ln(1\text{+exports/area})_e + \mathbf{X'}_{i,e,d,c}\Gamma + \mathbf{X'}_{d,c}\Omega + \mathbf{X'}_e\Phi + \varepsilon_{i,e,d,c}, \tag{10}$$

where the dependent variable $\text{trust}_{i,e,d,c}$ differs across the estimated equations. Specifically, the following equations are estimated:

$$\text{trust of relatives}_{i,e,d,c} = \alpha_c + \beta \ln(1\text{+exports/area})_e + \mathbf{X'}_{i,e,d,c}\Gamma + \mathbf{X'}_{d,c}\Omega + \mathbf{X'}_e\Phi + \varepsilon_{i,e,d,c}, \tag{11}$$

$$\text{trust of neighbors}_{i,e,d,c} = \alpha_c + \beta \ln(1\text{+exports/area})_e + \mathbf{X'}_{i,e,d,c}\Gamma + \mathbf{X'}_{d,c}\Omega + \mathbf{X'}_e\Phi + \varepsilon_{i,e,d,c}, \tag{12}$$

$$\text{trust of local council}_{i,e,d,c} = \alpha_c + \beta \ln(1\text{+exports/area})_e + \mathbf{X'}_{i,e,d,c}\Gamma + \mathbf{X'}_{d,c}\Omega + \mathbf{X'}_e\Phi + \varepsilon_{i,e,d,c}, \tag{13}$$

$$\text{intragroup trust}_{i,e,d,c} = \alpha_c + \beta \ln(1\text{+exports/area})_e + \mathbf{X'}_{i,e,d,c}\Gamma + \mathbf{X'}_{d,c}\Omega + \mathbf{X'}_e\Phi + \varepsilon_{i,e,d,c}, \tag{14}$$

$$\text{intergroup trust}_{i,e,d,c} = \alpha_c + \beta \ln(1\text{+exports/area})_e + \mathbf{X'}_{i,e,d,c}\Gamma + \mathbf{X'}_{d,c}\Omega + \mathbf{X'}_e\Phi + \varepsilon_{i,e,d,c}, \tag{15}$$

All estimated coefficients of interest, denoted by β in aforementioned equations, are negative, significant at a 1 percent level, and range from -0.00068 to -0.743. For further details, one can turn to Table 27 in the appendix. Table 3 of Nunn and Wantchekon (2011) considers the same relationship between the baseline measure for slave exports, $ln(1+exports/area)$ and the aforementioned measures of trust. Now, however, additional controls are included, namely ethnicity-level colonial controls, and controlling for colonial population density. The aforementioned equations are included in the regression. Again, all estimated coefficients are negative and significant at a 1 percent level.

Furthermore, tables 5 and 6 of Nunn and Wantchekon (2011) take the distance of an ethnic group to the coast as an instrument for the number of slaves captured, as they assume that distance from coast had an impact on trust only through slave trade. In order to validate the use of this instrumental variable, a number of falsification tests outside of Africa are considered. In the first stage of the IV regressions, the following equation is estimated:

$$\text{ln(1+exports/area)}_e = \alpha_c + \beta \text{historical distance coast}_e + \mathbf{X}'_{i,e,d,c}\Gamma + \mathbf{X}'_{d,c}\Omega + \mathbf{X}'_e\Phi + \varepsilon_{i,e,d,c}, \quad (16)$$

Additionally, equations 17 - 15 are used to estimate the coefficient of interest β in the second stage of the IV regressions. All estimates are negative and significant at a 1 percent level. Table 6 makes use of the same equations as in Table 5, both during the first and second stage of the IV regressions, but besides controls for reliance on fishing, and for distance to a Saharan city or historic route. All coefficients of tables 5 and 6 are negative and significant.

Table 7 and 8 are used as validation for the power of the instrumental variable *historical distance of ethnic group from coast*. Table 9 and 10 serve as tools to identify which channels are causing the investigated causality. Table 9 makes use of the same controls as Table 3, supplemented by council trustworthiness fixed effects, and five public goods fixed effects, which consist of school, health clinic, sewage, piped water, and electricity. Table 10 makes use of the same controls of Table 3 as well. To see which slave export and trust measures, as well as which controls are considered, one can turn to tables in the appendix.

3.2 The Rise of Europe

In Acemoglu et al. (2005), three models are introduced to capture the relationship between Atlantic trade in western Europe and its economical and political effects. Because the second model is a more restrictive version of the first model, only the following two models are considered in this paper. First, the following equation is estimated to keep track of the economic implications of Atlantic trade:

$$u_{jt} = d_t + \delta_j + \sum_{t \geq 1600} \alpha_t \cdot WE_j \cdot d_t + \beta \cdot PAT_j \cdot \ln AT_t + X'_{jt} \cdot \gamma + \varepsilon_{jt} \quad (17)$$

where u_{jt} denotes country j's urbanization at time t, WE_j is an indicator variable describing whether country j is in Western Europe, the d_t's denote year effects, δ_j denotes country fixed effects, X_{jt} is a covariate vector, and ε_{jt} is an error term. Furthermore, the variable PAT_j denotes the measure for Atlantic trade potential, which is an indicator variable for Atlantic trader (the Netherlands, Portugal, France, Britain, and Spain) or alternatively the Atlantic coastline-to-area ratio (both cases are time-invariant traits of the country). Additionally, AT_t represents an estimate of the aggregate volume of Atlantic trade, and the coefficient of interest β denotes the interaction term between log volume of Atlantic trade and potential for Atlantic trade at the country level.

In this paper, I will use equations 2 and 17 in order to apply DML techniques to Table 2, column 3 of Acemoglu et al. (2005), by replacing the variables in equation 2 to the ones in Table 2, column 3, which are based on equation 17. This causes the dependent variable Y to change to u_{jt} and the treatment variable D to change to PAT_t, for $t = 1500, 1600, 1700, 1750, 1800, 1850$. Again, important to note is that in Section 5 of Chernozhukov et al. (2017) a binary treatment variable is used, while our intended treatment variable takes on continuous values. This, however, is not an issue, since the provided code by Chernozhukov et al. (2017) is able to accept non-binary input for the treatment variable. Furthermore, the parameter of interest θ_0 changes to β_t, and the elements of vector X change to d_t, δ_t, and WE_j for the aforementioned t's. Unlike the regressions used in Nunn and Wantchekon (2011), the other treatment variables PAT_t that are not considered at time t are also added to the covariate vector X.

Second, to keep track of the political implications of Atlantic trade by western European countries, the following equation is estimated by Acemoglu et al. (2005):

$$u_{jt} = d_t + \delta_j + \sum_{t\geq 1600} \alpha_t \cdot WE_j \cdot d_t + \beta \cdot PAT_j \cdot \ln AT_t + \sum_{t\geq 1500} \gamma_t \cdot I_{j,1415} \cdot d_t + \eta \cdot PAT_j \cdot \ln AT_t \cdot I_{j,1415} + \varepsilon_{jt} \tag{18}$$

where the same variables as in equation 17 are used, supplemented by the variable $I_{j,1415}$, which denotes country j's initial institutions. This variable is calculated as the average of its constraint on the executive in 1400 and 1500, in order to capture the long-term institutional differences in the before 1500 period. The $\gamma_t \cdot I_{j,1415} \cdot d_t$ terms allow for any differential economic trends associated with differences in initial institutions that would apply without access to the Atlantic even.

3.3 Double/Debiased Machine Learning

To establish good behavior of the estimator of the treatment variable, DML techniques have to conform to certain moment conditions. Generalizing the orthogonal principle in section 3.4, one has to compare the solution of conventional equations to the solution of estimating the orthogonalized equations. The conventional equations can be represented as follows:

$$\frac{1}{n}\sum_{i\in I} \varphi(W;\hat{\theta}_0, \hat{g}_0) = 0, \tag{19}$$

where φ is a known "score" function and $\hat{g}_0$ is the estimator of the nuisance parameter g_0. This score function is sensitive to biased estimation of g as the Gâteaux derivative operator does not disappear:

$$\partial_g E_\varphi(W;\theta_0, g_0)[g - g_0] \neq 0 \tag{20}$$

By contrast, the double/debiased ML estimator $\hat{\theta}_0$ solves:

$$\frac{1}{n}\sum_{i\in I} \psi(W;\hat{\theta}_0, \hat{g}_0) = 0, \tag{21}$$

where $\hat{\eta}_0$ is the estimator of the nuisance parameter η_0 and ψ is an orthogonalized or debiased "score" function that causes the Gâteaux derivative operator to vanish:

$$\partial_\eta E_\psi(W;\theta_0, \eta_0)[\eta - \eta_0] = 0 \tag{22}$$

Equation 22 is also known as "Neyman orthogonality" and ψ as Neyman orthogonal score function. In the partial linear model in 1 and 2, the estimator $\hat{\theta}_0$ uses $\psi(W;\theta,\eta) = (Y - D\alpha - g(X))(D - m(X))$, with the nuisance parameter being $\eta = (m, g)$. It is clear to see that these score functions ψ are not sensitive to biased estimation of η_0 in the sense that equation 22 holds.

In short, Neyman orthogonality and moment conditions, together with sample splitting or "k-cross validation", make sure that the estimator of the parameter of interest is unbiased. In this paper, I use these moment conditions in order to apply DML to Nunn and Wantchekon (2011) and Acemoglu et al. (2005). The variables and parameters in this subsection change to the ones mentioned in equation 9 and 17.

3.4 Machine Learning Techniques

In order to apply DML to the data used in Nunn and Wantchekon (2011) and Acemoglu et al. (2005), I make use of several machine learning techniques. These techniques consist of the following methods: lasso, boosted trees, random forests, deep neural nets, and an ensemble method. In this paper, the ensemble method consist of the methods "RLasso", "Boosting", and "Forest". In the appendix, these techniques will be introduced and thoroughly explained.

Throughout my paper, I examine whether using these ML techniques on Nunn and Wantchekon (2011) and Acemoglu et al. (2005) provides significantly different results compared to the ones obtained by OLS regression.

The machine learning techniques mentioned in the appendix are implemented in the code provided by Chernozhukov et al. (2017). This code is used in the DML paper to provide empirical results supporting the theory. I have adjusted, however, this code in order to apply DML to the provided dataset by Nunn and Wantchekon (2011)[2] and Acemoglu et al. (2005)[3].

4 Data

4.1 Slave Trade Paper

The same data used in Nunn and Wantchekon (2011) will be used for its replication. These data consist of two sources: On one hand, the 2005 Afrobarometer surveys, which represent 17 sub-Saharan African nations based on interviews conducted in the local languages of a random sample of either 1200 or 2400 individuals of voting age in each country. In these interviews, individuals categorize their trust in their neighbors, relatives, and their elected government council.

On the other hand, estimates of the number of slaves collected from each ethnic group are based on country-level slave export data from Nunn (2008). In that paper, Nunn (2008) combines data on the total number of slaves shipped from all harbors and regions of Africa with data on the slaves' ethnic identities. Important to mention is the matching of ethnic identities in the historical data to the ethnic classification in the Afrobarometer surveys.

4.2 The Rise of Europe

In order to apply DML to the Rise of Europe paper, the data provided by Acemoglu et al. (2005) is used. These data consist of three sources.
First, urbanization estimates are constructed based on urban population figures found by Bairoch (1988). This dataset contains information about all 2200 European cities that had a minimum of 5000 inhabitants, at some time between 800 and 1800. These urban population numbers are then divided by McEvedy and Jones (1978)'s population estimates in order to calculate urbanization. Moreover, estimates of urbanization rates in Asia of Bairoch (1988) are used. Additionally, Acemoglu et al. (2002a) show that there is a close relationship between urbanization and income per capita, not only before but also after industrialization had occurred. Hence, urbanization is taken as a proxy for GDP per capita.
Second, estimates of GDP per capita from Maddison (2001) are used. They are available for 1500, 1600, 1700, 1820, and then more frequently. For these estimates are educational guesses, they serve the purpose of a check on the results using urbanization data.
Third, European city-level data from Bairoch (1988) is used in order to detect those urban centers that were driving economic and demographic growth. Additionally, these data were used to compare the growth of Atlantic harbors to other harbors and inland cities.

4.3 Adjusting Data and Code

Regarding the data provided by Nunn and Wantchekon (2011), I adjusted this data in order to estimate the examined relationship between slave exports in Africa and current trust-levels amongst Africans. First, by replicating the results in Stata, I obtained the dataset with several dummy variables for a respondent's education, occupation, religion, living conditions, isocode and several precolonial traits. This, and adding a constant variable to this dataset, resulted in an adjusted dataset of 21822 observations of 138 variables. Then, by omitting 'Not Available' observations for the used dependent variable, treatment variable, and covariates, a number of observations was established that equals the corresponding number of observations in Nunn and Wantchekon (2011).

[2] For provided dataset see: https://www.aeaweb.org/articles?id=10.1257/aer.101.7.3221
[3] For provided dataset see: https://www.aeaweb.org/articles?id=10.1257/0002828054201305

Regarding Acemoglu et al. (2005), running their dataset in Stata resulted in numerous dummies defining which countries and what years are considered. Furthermore, by adding a constant variable to this new dataset, I was able to implement a constant into the regression. In doing so, an adjusted dataset of 475 observations of 97 variables was created. By ordering the dataset after increasing values of the 'date' variable (from small to large), I was able to depict which rows confirmed to the conditions 'date'>1200 and 'date'<1900, which is stated in Table 2 of Acemoglu et al. (2005). Those rows that did not confirm to these conditions were excluded. The same procedure of ordering and excluding was applied to observations that did not confirm to the condition: 'asia' $\neq$ 1 i.e. excluding observations that describe Asian trading. Furthermore, the following country and year dummies were deleted due to collinearity issues: $country1$, $country11$, $country12$, $country18$, $country22$, $country28$, $yr1000$, $yr1100$, $yr1200$, and $yr1850$.

To apply double/debiased machine learning techniques to a low-dimensional parameter θ_0 in a high-dimensional nuisance parameter environment, I make use of the code provided by Chernozhukov et al. (2017). To properly run this code in *R*, the following packages had to be downloaded: *foreign*, *quantreg*, *mnormt*, *neuralnet*, *gbm*, *glmnet*, *MASS*, *rpart*, *doParallel*, *sandwich*, *hdm*, *randomForest*, *nnet*, *matrixStats*, *quadprog*, *xtable*, *dplyr*, *readstata13*. The R codes used to apply DML, which are adjusted versions of $Bonus.R$ and $AJR.R$[4], call the following functions: $MLFunctions.R$, which specifies the machine learning techniques used in the main code, and $MomentFunctions.R$, which consists of functions that estimate moments for using DML, as is thoroughly explained in the Methodology section, and also calls on $MLFunctions.R$. Furthermore, the number of sample splits has to be stated. Due to considerable running time issues, all results involving DML, which consist of replicating empirical results from Chernozhukov et al. (2017), and applying DML to Nunn and Wantchekon (2011) and Acemoglu et al. (2005), are conducted with a number of splits equal to 2. These running time issues for a larger number of splits are mainly due to the two slowest methods: 'Boosting' and, logically, the ensemble method, whereas 'Trees' computes results fastest for both small and large number of sample splits.

My used *R* code, after loading the required packages and dataset, adjusts the dataset by deleting 'Not Available' observations. Moreover, dependent variable 'y', treatment variable 'd', instrumental variable 'z', and control variable 'xl' (used for 'Lasso') and 'x' (used for other the methods) are specified.

Thereafter, the following machine learning techniques are used in my code for Nunn and Wantchekon (2011): Lasso, Trees, Boosting, Forest, and an ensemble method. For Acemoglu et al. (2005), the code also consists of the Neural Nets method. The ensemble method combines these four (five) other methods by estimating the nuisance functions as weighted averages of estimates obtained by these four methods. The weights are chosen in such a way that the weighted average of these methods yields the lowest average mean squared out-of-sample prediction error estimated using 5-fold cross-validation. Moreover, the weights are restricted to sum to one. These techniques are combined in an additional method 'Best', which selects the best methods for estimating each nuisance function based on the average out-of-sample prediction performance for the target variable.

When comparing the DML estimation results to the OLS estimated coefficients, the 'Best' method will be considered, as this method yields the best average out-of-sample prediction performance. Note that if a single ML method outperforms the others regarding prediction accuracy for all nuisance functions, the estimate under 'Best' will be equal to the estimate of that method. Also important to note is the absence of the 'Neuralnets' method for applying DML to Nunn and Wantchekon (2011). If this method was to be implemented, some variables containing 0 or 'Not Available' observations had to be deleted. Consequently, I decided not to include this method, as I regarded these variables to be essential for comparing the DML estimation results to the OLS estimation results. The ensemble method for Nunn and Wantchekon (2011) does not contain this method as well.

[4] For provided code see:https://github.com/VC2015/DMLonGitHub/

5 RESULTS

5.1 REPLICATING OLS AND EMPIRICAL RESULTS

Before applying DML to the provided datasets, I have replicated tables $1-3$, 5-6, and $9-10$ of Nunn and Wantchekon (2011) and tables $1-3$ and $5-6$ of Acemoglu et al. (2005) using Stata. The obtained results are shown in the appendix in tables 27 - 33 and 34 - 38. All tables control for at least the baseline controls, which consist of: controlling for individual traits, district characteristics and country fixed effects. As expected, the OLS replication yields similar results to those originally in Nunn and Wantchekon (2011) and Acemoglu et al. (2005), ensuring the proper use of both datasets. Appendix tables 27, 28, and 29 for Nunn and Wantchekon (2011) all show a negative relationship between different measures of slave trade and measures of trust-levels among Africans. The other tables indicate that this relationship is in fact causal. The same conclusion can therefore be drawn from the OLS replication: individuals whose ancestors were heavily raided during the slave trade are less trusting today. Furthermore, appendix tables 34 - 38 confirm the positive influence access to the Atlantic Ocean and the subsequent trade with Africa, Asia, and the New World via the Atlantic has had on economic and political growth.

Second, I also replicated the empirical results of the Chernozhukov et al. (2017) to ensure the proper use of the provided code. These results are depicted in the appendix tables 23, 24, 25 and 26. First, I ran the $Bonus.R$ code to replicate the empirical results in Chernozhukov et al. (2017) as in Table 1 of Section 6.1. The used dataset, $pennjae.dat$, contains 5099 observations of 23 variables. The results are captured in Table 23. As one can clearly see, the results are similar to the ones obtained in the DML paper, thus guaranteeing the proper use of the code.

To verify that the other provided codes are also properly used, I then tested the correctness of the $401K.R$ code by running it in R and comparing the obtained results with the ones as in Section 6.2 of the DML paper. The dataset Sipp1991.dta was used, which contains 9915 observations of 14 variables. Clearly, one sees that both uses of the code provide approximately similar results.

In addition to aforementioned replication of empirical results, I also replicated Table 3 of Section 6.3 of Chernozhukov et al. (2017) to show the validation of the code 401K-LATE.R. Again, the dataset Sipp1991.dta was used, containing 9915 observations of 14 variables. Running this code yields the results presented in Table 25. Again, similar results to the ones in Section 6.3 of the DML paper were obtained, ensuring the proper use of the 401K-LATE.R code.

Lastly, I have replicated Table 4 of the empirical results in Section 6.4 of Chernozhukov et al. (2017) by running the provided AJR.R code, with dataset AJR containing amongst others GDP and mortality rates. This yields the results as captured in Table 26. Again, approximately same results to those in section 6 of Chernozhukov et al. (2017) were obtained.

5.2 SLAVE TRADE PAPER

In this section, the results of tables 1, 2, and 5 of Nunn and Wantchekon (2011) are estimated using DML. The mentioned t-values are computed by dividing the estimated coefficient with its standard error. The following notation for significant coefficients is used:

- * : significant at 10 percent level
- ** : significant at 5 percent level
- *** : significant at 1 percent level

5.2.1 SLAVE TRADE DML REPLICATION OF TABLE 1

In this subsection, Table 1 of Nunn and Wantchekon (2011), in which OLS estimation is applied to examine the effect of different measures of slave exports on *trust neighbors*, is analyzed by using DML estimation. This table makes use of the aforementioned baseline controls. The obtained DML results are as follows:

	RLasso	Trees	Boosting	Forest	Ensemble	Best
Treatment Effect	-0.00029315	-0.00041043	-0.00055121	-0.00047586	-0.00043723	-0.00041981
Standard Error	(0.00028823)	(0.00038224)	(0.00034884)	(0.00039674)	(0.00034982)	(0.00037594)

Table 1: Applying DML to Table 1 coefficient 1: The Determinants of Trust in Neighbors

The first coefficient of Table 1 in Nunn and Wantchekon (2011) depicts the relationship between dependent variable *trust neighbors* and treatment variable *slave exports (thousands)*. OLS estimation yields a coefficient of -0.00068, which is not significant. As Table 1 shows that the coefficient estimated by 'Best' is somewhat smaller than this OLS coefficient, and with a t-value of $t = -1.126$, this coefficient fails to be significant. Furthermore, the coefficients do not differ much across these techniques. 'RLasso' yields the smallest effect, and due to a small standard error, this coefficient fails to be significant. As none of the DML techniques, just like OLS estimation, yield significant coefficients, there does not exist a major difference in results between using DML techniques and OLS estimation.

	RLasso	Trees	Boosting	Forest	Ensemble	Best
Treatment effect	-0.00346421	-0.00975123	-0.01194721	-0.01018604	-0.0111943	-0.01185931
Standard Error	(0.00504197)	(0.00631649)	(0.00810649)	(0.00920316)	(0.00878241)	(0.00897321)

Table 2: Applying DML to Table 1 coefficient 2: The Determinants of Trust in Neighbors

In Table 2, the possible relationship between dependent variable *trust neighbors* and treatment variable *exports/area* is shown, which yields a coefficient of -0.019 when using OLS estimation. With a standard error of 0.005, this OLS coefficient is significant at a 1 percent level. In 2, the 'Best' method yields an estimated treatment effect of -0.012, which fails to be significant. Consequentially, a different conclusion is drawn via DML estimation compared to OLS estimation, as DML does not show a significant relationship between *trust neighbors* and *exports/area*. Moreover, the other coefficients estimated using DML fail to be significant as well, and range from -0.012 to -0.0035.

	RLasso	Trees	Boosting	Forest	Ensemble	Best
Treatment Effect	-1.13276931***	-0.51769301***	-0.52864914**	-0.53121860**	-0.51887146**	-0.51286407**
Standard Error	(0.17593717)	(0.16420517)	(0.20890125)	(0.22674170)	(0.22330168)	(0.22959157)

Table 3: Applying DML to Table 1 coefficient 3: The Determinants of Trust in Neighbors

In Table 3, the relationship between dependent variable *trust neighbors* and *exports/hist pop* is illustrated. The estimated effect using OLS, as in Nunn and Wantchekon (2011), results in a 1 percent-level significant coefficient of -0.531. Likewise, 3 shows an estimated effect of -0.513 using the 'Best' method, and with a t-value equal to -2.29, this treatment effect also is significant, although at a 5 percent level. The effect estimated by 'RLasso' and 'Trees', however, is significant at a 1 percent level. In other words, DML estimation draws the same conclusion as OLS estimation, that there exists a negative relationship between *trust neighbors* and *exports/hist pop*.

	RLasso	Trees	Boosting	Forest	Ensemble	Best
Treatment Effect	-0.15665921***	-0.08172915***	-0.07929812***	-0.05967040**	-0.07194555**	-0.07198104**
Standard Error	(0.02726014)	(0.02664016)	(0.0281241)	(0.02854493)	(0.02901513)	(0.0295146)

Table 4: Applying DML to Table 1 coefficient 4: The Determinants of Trust in Neighbors

Table 4 investigates the relation between dependent variable *trust neighbors* and treatment variable *ln(1+exports/area)*. In Nunn and Wantchekon (2011), the coefficient of interest, estimated using OLS, equals -0.037, which is significant at a 1 percent level. The 'Best' method in Table 4 produces a much more negative coefficient of -0.072, which is 1.9 times more negative, but, due to a large standard error of 0.030, this coefficient is less significant (at 5 percent). Other DML techniques produce all negative, significant coefficients as well, ranging from -0.16 to -0.060.

Conclusively, DML yields a much more negative relationship, but due to a larger standard error, this relationship may be less reliable.

	RLasso	Trees	Boosting	Forest	Ensemble	Best
Treatment Effect	-0.29005216***	-0.14841941***	-0.17519514***	-0.14311183***	-0.1631960***	-0.14841065***
Standard Error	(0.03592065)	(0.03740631)	(0.04285063)	(0.04672054)	(0.04501974)	(0.05073179)

Table 5: Applying DML to Table 1 coefficient 5: The Determinants of Trust in Neighbors

Table 5 describes the relationship between dependent variable *trust neighbors* and treatment variable *ln(1+exports/area)*. The 'Best' method yields a coefficient of -0.15, and with a t-value of -2.93 this coefficient is significant at a 1 percent level. As the estimated effect in Nunn and Wantchekon (2011) using OLS is also 1 percent significant, and with an OLS coefficient of -0.159, the same conclusion can be drawn when using DML estimation: there exists a significant relationship between *trust neighbors* and *ln(1+exports/area)*.

	RLasso	Trees	Boosting	Forest	Ensemble	Best
Treatment Effect	-2.01704169***	-1.43950158***	-1.41850379***	-1.43019678***	-1.44019614***	-1.43943019***
Standard Error	(0.13496147)	(0.16019681)	(0.16619402)	(0.18015856)	(0.16701842)	(0.16810437)

Table 6: Applying DML to Table 1 coefficient 6: The Determinants of Trust in Neighbors

Table 6 shows the relationship between *trust neighbors* and *ln(1+exports/hist pop)*. Using OLS estimation, Nunn and Wantchekon (2011) finds a 1 percent significant relationship, with a coefficient equal to -0.743. Moreover, applying DML estimation results in much more negative coefficients. For instance, using the 'Best' method yields a coefficient of -1.44, while significant at at 1 percent level. Therefore, a much more profound, negative relationship between *trust neighbors* and *ln(1+exports/hist pop)* is found by DML. All coefficients are more negative than the OLS coefficient, are significant at a 1 percent level and range from -2.02 to -1.42.

5.2.2 Slave Trade DML replication of Table 2

In this subsection, Table 2 of Nunn and Wantchekon (2011), in which the effect of the baseline measure of exports, $ln(1 + exports/area)$, on different measures of trust is depicted using OLS estimation, is analyzed by using DML estimation. This table also makes use of the baseline controls. This produces the following results:

	RLasso	Trees	Boosting	Forest	Ensemble	Best
Treatment Effect	-0.40196582***	-0.26914065***	-0.22501479***	-0.21053868***	-0.21871492***	-0.2160142***
Standard Error	(0.031914232)	(0.02979140)	(0.02751021)	(0.02679158)	(0.02749167)	(0.02740186)

Table 7: Applying DML to Table 2 coefficient 1: The Determinants of the Trust of Others

Table 7 shows the influence of the baseline measure of slave exports, *ln(1+exports/area)*, as a treatment variable on dependent variable *trust neighbors*. This relationship is estimated in Nunn and Wantchekon (2011) using OLS and yields a coefficient of -0.133, which is significant at a 1 percent level. As shown in Table 7, all DML techniques also provide negative and 1 percent significant coefficients. Nonetheless, with an estimated coefficient of -0.22 using the 'Best' method, this relationship is much more thorough, as this effect is approximately 1.7 times larger than the OLS estimated effect. Likewise, the other DML techniques provide very negative coefficients, ranging from -4.0 till -0.21.

	RLasso	Trees	Boosting	Forest	Ensemble	Best
Treatment Effect	-0.46501978***	-0.25716494***	-0.2618306***	-0.23501988***	-0.19874846***	-0.24868474***
Standard Error	(0.03591604)	(0.03401982)	(0.03196403)	(0.03046916)	(0.02965121)	(0.02950197)

Table 8: Applying DML to Table 2 coefficient 2: The Determinants of the Trust of Others

Tabel 8 depicts the relationship between the treatment variable *ln(1+exports/area)* and dependent variable *trust neighbors*. In Nunn and Wantchekon (2011), this effect, using OLS estimation, is described by a 1 percent significant coefficient of −0.159. Similarly, the 'Best' method of applying DML provides a coefficient of −0.25. With a t-values of −8.4, this coefficient, just like the coefficients obtain using the other DML methods, is highly significant at a 1 percent level. Consequently, the same conclusion can be drawn when DML is applied instead of OLS i.e. there exists a significant negative relationship between *trust neighbors* and the baseline measure of slave exports *ln(1+exports/area)*.

	RLasso	Trees	Boosting	Forest	Ensemble	Best
Treatment Effect	-0.29601548***	-0.14593016***	-0.1470315***	-0.13201689***	-0.14306491***	-0.14310658***
Standard Error	(0.03263718)	(0.03040195)	(0.02819501)	(0.01930151)	(0.02519301)	(0.02631940)

Table 9: Applying DML to Table 2 coefficient 3: The Determinants of the Trust of Others

Table 9 describes the effect of *ln(1+exports/area)* on *trust local council*. OLS regression yields a 1 percent significant coefficient of −0.111, as shown in Table 2 of Nunn and Wantchekon (2011). Likewise, the 'Best' method provides an approximately similar coefficient of −0.143, with also is significant at a 1 percent level, due to a standard error of 0.026. This, together with the similar results obtained by the other DML techniques, causes the same conclusion in Nunn and Wantchekon (2011) to be drawn when using DML.

	RLasso	Trees	Boosting	Forest	Ensemble	Best
Treatment Effect	-0.38910241***	-0.187912041***	-0.19315960***	-0.16849104***	-0.18381940***	-0.17912039***
Standard Error	(0.03501691)	(0.03221950)	(0.02949301)	(0.02812590)	(0.02772910)	(0.02841051)

Table 10: Applying DML to Table 2 coefficient 4: The Determinants of the Trust of Others

In Table 10, the effect of *ln(1+exports/area)* on *intragroup trust* is estimated using DML techniques. The coefficient estimated by the 'Best' method equals −0.18, and with a t-value of −6.3, this coefficient is highly significant. Moreover, this coefficient does not differ much from the coefficient in Nunn and Wantchekon (2011) using OLS regression, which equals −0.144 and is significant at a 1 percent level as well. Therefore, the same negative relationship between *ln(1+exports/area)* and *intragroup trust* can be concluded from DML.

	RLasso	Trees	Boosting	Forest	Ensemble	Best
Treatment Effect	-0.35491581***	-0.20501293***	-0.18912057***	-0.18129851***	-0.18361354***	-0.19571389***
Standard Error	(0.03591205)	(0.02982015)	(0.02830198)	(0.02911921)	(0.02712859)	(0.02987211)

Table 11: Applying DML to Table 2 coefficient 5: The Determinants of the Trust of Others

Table 11 describes the fifth and final coefficient of Table 2 in Nunn and Wantchekon (2011), which captures the effect of *ln(1+exports/area)* on *intergroup trust*. In Nunn and Wantchekon (2011), this relationship is described by a 1 percent significant OLS coefficient of −0.097, whereas the 'Best' method of DML produces a much more negative coefficient of −0.196, which is approximately 2 times larger than the corresponding OLS coefficient. With a t-value of −6.55, this DML coefficient is also 1 percent significant. Consequently, using DML draws a similar, but more profound conclusion i.e. the estimated negative influence of *ln(1+exports/area)* on *intergroup trust* is much larger.

5.2.3 Slave Trade DML replication of Table 5

In this section, the results of applying DML to Table 5 of Nunn and Wantchekon (2011), in which results are estimated using instrumental variable regressions, are shown. In addition to the baseline controls, this table controls for colonial population density and makes use of ethnicity-level colonial controls.

	RLasso	Trees	Boosting	Forest	Ensemble	Best
Treatment Effect	0.04491581	-0.07120491***	-0.07348192***	-0.08738199***	0.02237310	0.02259139
Standard Error	(0.03911351)	(0.02031567)	(0.01812950)	(0.02359120)	(0.03949341)	(0.03949130)

Table 12: Applying DML to Table 5 coefficient 1: IV estimates of the effect of Slave Trade on Trust

Table 12 shows the estimation results of using DML with treatment variable *ln(1+exports/area)*, dependent variable *trust relatives* and as instrumental variable the *hist dist to coast* is taken. In Table 5 of Nunn and Wantchekon (2011), IV estimation produces a coefficient of interest of −0.190, which is significant at a 1 percent level. The 'Best' method in Table 12, however, yields a positive constant of 0.023, which is surprising since, intuitively, one does not expect slave trade to be positively correlated with trust-levels. With a t-value of 0.57, this coefficient is not significant, which may explain the unexpected positive coefficient. On top of that, the DML methods that are significant all show negative treatment effects. Thus Table 12 does not support nor reject the conclusion of a negative relationship between the baseline measure of exports and *trust relatives*.

	RLasso	Trees	Boosting	Forest	Ensemble	Best
Treatment Effect	0.03739105	-0.07419274***	-0.1131931***	-0.12742315***	-0.0653488	-0.0641120
Standard Error	(0.0404319)	(0.02129414)	(0.01949302)	(0.02448391)	(0.04048923)	(0.04185933)

Table 13: Applying DML to Table 5 coefficient 2: IV estimates of the effect of Slave Trade on Trust

In Table 13, the relationship between the baseline measure of slave exports and *trust neighbors* is depicted. In Table 5 of Nunn and Wantchekon (2011), this relationship is estimated by IV regression, which provides a 1 percent significant coefficient of −0.245. This negative effect is supported by Table 13, which shows all negative treatment effects, except for a positive, but insignificant coefficient produced by the 'RLasso' method. As the 'Best' method yields a treatment effect of −0.064 with a t-value of −1.53, the negative relationship between *ln(1+exports/area)* and *trust neighbors* is not sufficiently supported due to insignificant treatment effects.

	RLasso	Trees	Boosting	Forest	Ensemble	Best
Treatment Effect	-0.21493012***	-0.23392012***	-0.22859261***	-0.22489211***	-0.24038912***	-0.24038493***
Standard Error	(0.04541031)	(0.02419501)	(0.02249201)	(0.02710483)	(0.04531450)	(0.04539102)

Table 14: Applying DML to Table 5 coefficient 3: IV estimates of the effect of Slave Trade on Trust

Table 14 shows the effect of *ln(1+exports/area)* on *trust local council*, with the *historical distance of ethnic group from coast* used as an instrumental variable. The 'Best' method yields a result of −0.24, which is significant at a 1 percent level as its t-value equals −5.30. Similarly, the corresponding OLS coefficient in Table 5 of Nunn and Wantchekon (2011), which equals −0.221, is highly significant at a 1 percent level. As both DML and OLS produce approximately similar results, and because the coefficients obtained using different DML techniques do not differ much, the same conclusion of a negative relationship can be drawn from Table 14.

	RLasso	Trees	Boosting	Forest	Ensemble	Best
Treatment Effect	-0.02564921	-0.13710492***	-0.15193011***	-0.13905833***	-0.07841213**	-0.07841213**
Standard Error	(0.04030194)	(0.02183910)	(0.02112344)	(0.02502914)	(0.0391280)	(0.0391280)

Table 15: Applying DML to Table 5 coefficient 4: IV estimates of the effect of Slave Trade on Trust

Table 15 describes the influence of the baseline measure of slave exports, *ln(1+exports/area)*, and the *intragroup trust* measurement. This relationship estimated by IV estimation, as in Table 5 of Nunn and Wantchekon (2011), yields a highly significant coefficient of −0.251. Likewise, the 'Best' method in Table 15 produces a negative coefficient of −0.78. Therefore, Table 15 endorses the same conclusion drawn by Table 5, however, due to a 5 percent significant, and less negative 'Best' coefficient, this conclusion is stated less profoundly. Note that this coefficient equals the 'Ensemble' coefficient, as this method outperforms the other methods regarding average out-of sample prediction performance.

	RLasso	Trees	Boosting	Forest	Ensemble	Best
Treatment Effect	0.12940481	-0.01920391	-0.02039130	-0.02729301	0.08501299*	0.08749130*
Standard Error	(0.04391349)	(0.02149341)	(0.0201431)	(0.02513135)	(0.04391581)	(0.05539103)

Table 16: Applying DML to Table 5 coefficient 5: IV estimates of the effect of slave trade on trust

Table 16 shows the influence of treatment variable *ln(1+exports/area)* on dependent variable *intergroup trust*. In Table 5 of Nunn and Wantchekon (2011), this coefficient, estimated using IV, equals -0.174 and is significant at a 10 percent level. The 'Best' estimate in Table 16 equals 0.087, but with a t-value of 1.58, this coefficient fails to be significant. This may explain the unexpected positive relationship between slave trade and trust. Conclusively, DML replication cannot confirm nor reject the conclusion of a positive relationship between *ln(1+exports/area)* and *intergroup trust* obtained by OLS estimation.

5.3 The Rise of Europe

In this section, the results of table 2 of Acemoglu et al. (2005) are estimated using DML. The following notation for significant coefficients is used:

- * : significant at 10 percent level
- ** : significant at 5 percent level
- *** : significant at 1 percent level

5.3.1 Rise of Europe DML replication of Table 2, column 3

In this section, the results of applying DML to Table 2, column 3 of Acemoglu et al. (2005) are depicted. As dependent variable, the country-level *urbanization* is taken, and as treatment variable, the potential for Atlantic trade is taken over different years t. Further details about variables involved, are described in the Methodology section.

	RLasso	Trees	Boosting	Forest	Nnet	Ensemble	Best
Treatment Effect	0.00093197	8.364e-05	0.00115032	0.0007272*	0.00055991**	0.00138209*	0.00114283
Standard Error	(0.00087984)	(0.00025389)	(0.00078642)	(0.00043402)	(0.00028359)	(0.00078342)	(0.00076547)

Table 17: Applying DML to Table 2 column 3, coefficient 1: Atlantic trade and Urbanization

In Table 17, six double/debiased machine learning techniques are applied to Table 2, column 3 of Acemoglu et al. (2005), plus a 'Best' method, combining the methods to yield the best result regarding average out-of-sample prediction performance. The first coefficient describes the possible relationship between dependent variable *urbanization* and treatment variable PAT1500, a dummy describing potential for Atlantic trade in 1500. This coefficient estimated by OLS, as in Acemoglu et al. (2005), equals 0.016 and is not significant due to a t-value of 0.76. As stated in Table 17, the 'Best' method produces a coefficient of 0.0011, which is not significant. Therefore, the estimated effect by DML is similar compared to OLS estimation, thus the same conclusion that there does not exist a significant relationship between PAT1500 and *urbanization* can be drawn.

	RLasso	Trees	Boosting	Forest	Nnet	Ensemble	Best
Treatment Effect	0.00071850*	0.00029127	0.00068883	0.00020821	0.00044711	0.00020299	0.00085595
Standard Error	(0.00037748)	(0.00025801)	(0.00186911)	(0.00057435)	(0.00029181)	(0.00026411)	(0.0025793)

Table 18: Applying DML to Table 2 column 3, coefficient 2: Atlantic trade and Urbanization

The estimated coefficient of Table 2 of Acemoglu et al. (2005), which is shown in Table 13, describes the possible influence of dummy variable PAT1600 on *urbanization*, and equals 0.006 when estimated using OLS. With a standard error of 0.023, this coefficient is not significant in Acemoglu et al. (2005). Likewise, estimating this relationship using the 'Best' DML technique yields a non significant coefficient of 0.00086. Therefore, no significant different conclusion between DML and OLS can be drawn.

	RLasso	Trees	Boosting	Forest	Nnet	Ensemble	Best
Treatment Effect	0.00081566**	0.00046631*	0.00157424	8.2e-05	0.00023965	0.00041452	0.00041452
Standard Error	(0.00041092)	(0.00025826)	(0.00203929)	(0.00049344)	(0.00031211)	(0.00026751)	(0.00026751)

Table 19: Applying DML to Table 2 column 3, coefficient 3: Atlantic trade and Urbanization

In Table 19, the possible relation between dependent variable *urbanization* and treatment variable PAT1700 is illustrated. In Acemoglu et al. (2005), this relationship yields a non-significant coefficient of 0.032. Besides, estimating this influence using DML provides a non-significant coefficient of 0.00041. Note that this coefficient equals the 'Ensemble' coefficient, as this method outperforms the other methods. Therefore, the same conclusion as in Acemoglu et al. (2005) may be drawn, that the potential for Atlantic trade in 1700 does not have significant influence on country-level urbanization.

	RLasso	Trees	Boosting	Forest	Nnet	Ensemble	Best
Treatment Effect	0.00073145	0.0024088	0.00265073	0.00569058	0.05644388	0.01392618	0.02847844
Standard Error	(0.02163872)	(0.01788663)	(0.01331804)	(0.02835258)	(0.04029227)	(0.02420537)	(0.03856443)

Table 20: Applying DML to Table 2 column 3, coefficient 4: Atlantic trade and Urbanization

Table 20 uses DML to estimate the possible relationship between treatment variable PAT1750 and country-level *urbanization*, which yields an OLS coefficient of 0.032, whereas DML estimation provides a coefficient of 0.028. Both coefficients are similar in value and not significant, thus the same conclusion of a not significant effect can be drawn by DML as well as OLS estimation.

	RLasso	Trees	Boosting	Forest	Nnet	Ensemble	Best
Treatment Effect	0.0160856	0.00015093	0.00306622	0.02872649	0.02763679	0.03208941	0.02763679
Standard Error	(0.02671498)	(0.02173214)	(0.02271309)	(0.04163544)	(0.0366209)	(0.03751121)	(0.0366209)

Table 21: Applying DML to Table 2 column 3, coefficient 5: Atlantic trade and Urbanization

Table 21 shows the possible relationship between dependent variable *urbanization* and treatment variable PAT1800, which yields a 5 percent significant OLS coefficient of 0.048. With a t-value of 0.75, the DML coefficient estimated by the 'Best' method, which equals 0.028 fails to be significant. Therefore, DML cannot endorse the conclusion of Acemoglu et al. (2005), which states that a potential Atlantic trader in 1800 is positively correlated with *urbanization*.

	RLasso	Trees	Boosting	Forest	Nnet	Ensemble	Best
Treatment Effect	0.01606023	0.01536904	0.02713653	0.05377637	0.0410558	0.05870471	0.05870471
Standard Error	(0.02825376)	(0.0273625)	(0.0376909)	(0.04285481)	(0.07175434)	(0.04430209)	(0.04430209)

Table 22: Applying DML to Table 2 column 3, coefficient 6: Atlantic trade and Urbanization

Table 22 provides estimation results for dependent variable *urbanization* and treatment variable PAT1850. The estimated 'Best' coefficient equals 0.059 and with a t-value of 1.33, this coefficient fails to be significant. Note that this coefficient has the same value as the one produced by the 'Ensemble' method, showcasing the outperforming of other methods by 'Ensemble'. As the corresponding OLS coefficient, which equals 0.085, is highly significant, the positive effect of a potential Atlantic trader in 1850 on urbanization, concluded by OLS estimation, cannot be confirmed by DML.

6 Conclusion

As shown in the Results section for Nunn and Wantchekon (2011), DML produces more profound and significant relationships between dependent variable and associated treatment effect in most cases. This shows the complimentary effect DML has compared to classical econometric estimation methods, questioning their trustworthiness, and showing the relevance of applying DML to research in a social economic framework. Regarding the results for Acemoglu et al.

(2005), since DML provides insignificant coefficients in most cases, this does not show the relevance of double/debiased machine learning for treatment effects' applications. Therefore, the conclusions reached in Nunn and Wantchekon (2011) are disputed, casting doubt about the reliability of classical econometric methods, whereas those in Acemoglu et al. (2005) are not. From this difference in conclusions, one may argue that researchers should consider using DML more frequently in a framework of many covariates and/or big datasets.

Nonetheless, in the process of expanding the theory behind double/debiased machine learning and its applications, this paper contributes in empirically validating its relevance, by questioning the trustworthiness of OLS and IV estimation compared to DML. This paper, however, is prone to several points of improvements. First, as a used number of sample splits of 2 is fairly low, conducting this same research may yield substantially different results when using the same number of splits. Moreover, increasing the number of splits would improve the trustworthiness of this paper, due to running time issues, however, this was not achievable at this time.

Second, as the neural nets machine learning method required the exclusion of certain vital covariate variables for Nunn and Wantchekon (2011), I decided not to include this method. Luckily, this method was applicable to Acemoglu et al. (2005), but for a more robust empirical validation of this method, neural nets would have to be applied to more papers to clearly evaluate its usefulness.

Third, estimating the treatment effect for several equations in Acemoglu et al. (2005), resulted in many insignificant coefficients. This may be due to the fact that Acemoglu et al. (2005) only uses about 4 covariates. Moreover, the unadjusted dataset of Acemoglu et al. (2005) contains only 475 observations. The applied machine learning techniques do not cope well with both these characteristics within a framework of low-dimensional nuisance parameters. Therefore, a different paper, which uses more covariates and/or a bigger dataset, may be more suitable.

Lastly, regarding the content of these two social economic papers, I noticed that Nunn and Wantchekon (2011) only investigates the possible relationship of slave trade and the social and political state of Africa today through its effect on trust-levels amongst Africans. Interestingly, this may not be the only trustworthiness factor that has been eroded due to slave trade. For instance, further research into Africans trustworthiness of Europeans may be interesting, or, since Africans were also enslaved by Arabs (Martin and Ryan, 1977), researching the trustworthiness of Arabs by (Eastern) Africans can be of interest, to potentially support or reject the social impact that slave trade has had in Africa.

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Appendices

A Machine Learning Techniques

A.0.1 LASSO

The "Least Absolute Selection and Shrinkage Operator", or LASSO, is a technique which is used often in econometrics. One reason is because LASSO yields few non-zero estimates, so one can discuss which covariates matter most. LASSO makes use of the standard linear equation $Y_i = X_i'\beta + \varepsilon$ in order to estimate the coefficient of interest β. This estimation minimizes the following formula with respect to β:

$$\sum_{i=1}^{N}(Y_i - X_i\beta)^2 + \lambda\|\beta\|_1 \tag{23}$$

where the L_1 norm is used, which is a specification of the L_P norm: $\|x\|_p = (\sum_{k=1}^{K}|x_k|^p)^{\frac{1}{p}}$

A.0.2 Regression Trees

The main idea behind the technique of regression trees is to sequentially partition the covariate space into subspaces where the regression function is estimated as the average outcome for units with covariate values in that subspace.

First, one defines for covariate k and threshold t the estimator:

$$g_{k,t}(x|\mathbf{X},\mathbf{Y}) = \bar{Y}_{left} I(x_{k(\mathbf{X},\mathbf{Y})} \leq t(\mathbf{X},\mathbf{Y})) + \bar{Y}_{right} I(x_{k(\mathbf{X},\mathbf{Y})} > t(\mathbf{X},\mathbf{Y})) \tag{24}$$

where

$$\bar{Y}_{left} = \frac{\sum_{i:X_{i,k}\leq t} Y_i}{\sum_{i:X_{i,k}\leq t} 1} \qquad \bar{Y}_{right} = \frac{\sum_{i:X_{i,k}> t} Y_i}{\sum_{i:X_{i,k}> t} 1} \tag{25}$$

Consequently, one can find the covariate k^* and the threshold t^* that solve $(k^*, t^*) = \arg\min_{k,t} Q(g_{k,t}(\cdot))$, where the function $Q(g)$ is the sum of squared deviations. By solving this equation, one can keep splitting the covariate space into two subspaces, by whether $X_{i,k^*} \leq t^*$ or not. Consecutively dividing subspaces minimizes the objective function, with a penalty term: $Q(g) + \lambda *$ (number of leaves).

A.0.3 Boosted Trees

The boosted trees technique makes use of a so-called *weak learner*: a simple, possible naive way of estimating a regression function. Boosting is a general approach to repeatedly use the weak learner to get a good predictor for both classification and regression problems. Suppose $g(x|\mathbf{X},\mathbf{Y})$ is based on a regression tree with only a single split. The algorithm selects a covariate $k(\mathbf{X},\mathbf{Y})$ and a threshold $t(\mathbf{X},\mathbf{Y})$ and then estimates the regression function as in 30.

Thereafter, one defines the residual relative to this weak learner as $\varepsilon_{1i} = Y_i - g_1(X_i|\mathbf{X},\mathbf{Y})$. Now apply the *same* weak learner to the *new* data set $(\mathbf{X},\varepsilon_1)$. By repetitively growing new trees, defining the residuals and re-applying the weak learner to the new dataset, one obtains an additive approximation to the regression function $g(x|\mathbf{X},\mathbf{Y})$:

$$\sum_{m=1}^{M} g_m(x|\mathbf{X},\varepsilon_{m-1}) = \sum_{k=1}^{K} h_k(x_k) \qquad \text{where} \quad \varepsilon_0 = \mathbf{Y} \tag{26}$$

A.0.4 Random Forests

Given data $(\mathbf{X},\mathbf{Y})$, with dimension of $\mathbf{X}$ equaling $N \times K$, the random forests method constructs a tree starting with a single leaf in the following manner:

1. Randomly select L regressors out of the set of K regressors
2. Select the optimal covariate and threshold among L regressors
3. If some leaves have more than N_{min} units, go back to step (1)
4. Otherwise stop

A.0.5 Deep Neural Nets

The deep neural nets method uses the following relationship between X_i and Y_i through hidden layers of Z_i:

$$Z_{i,m} = \sigma(\alpha_{0m} + \alpha'_{1m} X_i), \quad \text{for} \quad m = 1, ..., M \tag{27}$$

$$Y_i = \beta_0 + \beta'_1 Z_i + \varepsilon_i \tag{28}$$

So the Y_i are linear in a number of transformations of the original covariates X_i. The parameters α and β are valued by minimizing:

$$\sum_{i=1}^{N} (Y_i - g(X_i, \alpha, \beta))^2 \tag{29}$$

Estimation using Neural Nets, however, can be hard. One possible drawback of this method, however, is the risk of overfitting. This can be solved by adding a penalty term to formula 15.

A.0.6 Ensemble Methods

The ensemble methods make use of a number M candidate estimators $g_m(\cdot|\mathbf{X}, \mathbf{Y})$ and combine them to obtain a better estimator than the one obtained by using any single algorithm. The involved methods can be similar, such as trees, but may also very well be qualitatively different, for instance some trees, some neural networks and some regression models. This requires assigning weights to the different methods, which can be constructed in the following way:

$$\min_{\alpha_1, ..., \alpha_M} \sum_{i=1}^{N} \left(Y_i - \sum_{m=1}^{M} \alpha_m \cdot g_m(X_i) \right)^2 \tag{30}$$

In case of many algorithms to choose from, regularizing this case by adding a LASSO-type penalty term may be useful. This results in a weighted average that puts non-zero weights on only a few models.

B Replicating Empricial results DML

	RLasso	Trees	Forest	Boosting	Nnet	Ensemble	Best
ATE	-0.0842	-0.0852	-0.0745	-0.0740	-0.0778	-0.0756	-0.0740
SE	0.0358	0.0359	0.0356	0.0354	0.0353	0.0354	0.0354
MSE[Y|X]	1.214	1.215	1.215	1.200	1.208	1.200	1.215
MSE[D|X]	0.475	0.474	0.479	0.474	0.478	0.474	0.474

Table 23: Replicating empirical results Table 1 by running Bonus.R

	RLasso	Trees	Forest	Boosting	Nnet	Ensemble	Best
ATE	7715	8494	8557	8519	9374	8859	9046
SE	1419	1371	1274	1321	1308	1295	1286
MSE[Y|X]	57283	57528	54284	54961	53520	53711	63516
MSE[D|X]	0.4488	0.4497	0.4516	0.4436	0.4482	0.4433	0.4832

Table 24: Replicating empirical results Table 2 by running 401K.R

	RLasso	Trees	Forest	Boosting	Nnet	Ensemble	Best
ATE	10393	10942	11661	11363	12157	11467	11480
SE	28011	1768	1796	1606	1909	1596	1605
MSE[Y|X,Z=0]	50050	51238	48508	26139	48887	46407	63936
MSE[Y|X,Z=1]	67756	68529	64107	64613	64841	64890	64696
MSE[D|X,Z=0]	0.000	0.000	0.000	0.000	0.000	0.000	0.000
MSE[D|X,Z=1]	0.453	0.453	0.462	80490	0.461	0.449	0.624
MSE[Z|X]	0.452	0.450	0.452	0.443	0.447	0.442	0.483

Table 25: Replicating empirical results Table 3 by running 401K-LATE.R

	RLasso	Trees	Boosting	Forest	Nnet	Ensemble	Best
ATE	0.955	0.824	0.699	1.141	1.039	1.114	1.115
SE	0.166	0.227	0.218	0.528	0.276	0.512	0.516
MSE[Y|X]	1.056	0.868	0.829	0.833	0.906	0.824	NA
MSE[D|X]	1.467	1.457	1.389	1.343	1.423	1.346	NA
MSE[Z|X]	1.211	1.173	1.005	0.912	1.068	0.933	NA

Table 26: Replicating empirical results Table 4 by running AJR.R

C Replicating OLS results Slave Trade paper

Dependent variable: trust of neighbors	Slave exports (thousands) (1)	Exports/ area (2)	Exports/ historical pop (3)	ln(1+ exports) (4)	ln(1+ exports/ area) (5)	ln(1+exports/ historical pop) (6)
Estimated coefficient	−.000679	−.0188	−.531	−.0374	−.159	−.743
Robust Standard Error	.000142	.00510	.147	.0138	.0339	.187
Number of observations	20,027	20,027	17,644	20,027	20,027	17,644
Number of ethnicities	185	185	157	185	185	157
Number of districts	1,257	1,257	1,214	1,257	1,257	1,214
R-squared	0.156	0.156	0.147	0.150	0.156	0.147

Table 27: OLS replication of Table 1 in Slave Trade Paper, including controlling for the baseline controls.

	Trust of relatives (1)	Trust of neighbors (2)	Trust of local council (3)	Intra-group trust (4)	Inter-group trust (5)
ln(1+exports/area)	−.133	−.159	−.111	−.144	−.0969
Robust Standard Error	.0360	.0339	.0216	.0315	.0278
Number of observations	20,062	20,027	19,733	19,952	19,765
Number of ethnicity clusters	185	185	185	185	185
Number of district clusters	1,257	1,257	1,283	1,257	1,255
R-squared	0.133	0.156	0.196	0.144	0.112

Table 28: OLS replication of Table 2 in Slave Trade Paper, including controlling for the baseline controls.

	Trust of relatives (1)	Trust of neighbors (2)	Trust of local council (3)	Intra-group trust (4)	Inter-group trust (5)
ln(1+exports/area)	−.178	−.202	−.129	−.188	−.115
Robust Standard Error	.0198	.0299	.0211	.0317	.0299
Number of observations	16,709	16,679	15,905	16,636	16,473
Number of ethnicity clusters	147	147	146	147	147
Number of district clusters	1,187	1,187	1,194	1,186	1,184
R-squared	0.130	0.160	0.206	0.155	0.119

Table 29: OLS replication of Table 3 in Slave Trade Paper, including baseline controls, colonial population density, and colonial controls for ethnicity-level.

Besides, I have replicated Tables 5 and 6 with two-step IV regression by running the .do file in Stata and saving the results. These results are captured in tables 30 and 31, as shown below. In Table 30, the following controls are taken into account: district controls, individual controls, colonial controls for ethnicity-level, measures for colonial population density and country fixed effects. In Table 31, not only are these controls taken into account, but also reliance on fishing and the distance to a Saharan city/route. In both tables, the historical distance of an ethnic group from the coast is taken as an instrumental variable.

	Trust of relatives (1)	Trust of neighbors (2)	Trust of local council (3)	Intra-group trust (4)	Inter-group trust (5)
Second stage: Dependent var.: individual's trust					
ln(1+exports/area)	−.190	−.245	−.221	−.251	−.174
Robust Standard Error	.0673	.0705	.0599	.0876	.0806
R-squared	0.130	0.159	0.204	0.154	0.118
First stage: Dependent var. : ln(1+exports/area)					
Historical distance of ethnic group from coast	−.00139 (.000268)	−.00138 (.000268)	−.00138 (.000263)	−.00139 (.000268)	−.00139 (.000267)
Number of observations	16,709	16,679	15,905	16,636	16,473
Number of clusters	147/1,187	147/1,187	146/1,194	147/1,186	147/1,184
R-squared	0.807	0.807	0.810	0.807	0.807

Table 30: IV replication of Table 5 in Slave Trade Paper, including baseline controls, colonial controls for etnicity-level, and colonial population density.

	Trust of relatives (1)	Trust of neighbors (2)	Trust of local council (3)	Intra-group trust (4)	Inter-group trust (5)
Second stage: Dependent variable: individual's trust					
ln(1+exports/area)	−.172	−.271	−.262	−.254	−.189
Robust Standard Error	.0758	.0881	.0750	.109	.103
R-squared	0.131	0.158	0.203	0.155	0.118
First stage: Dependent variable: ln(1+exports/area)					
Historical distance of ethnic group from coast	−.00147 (.000316)	−.00147 (.000316)	−.00145 (.000308)	−.00148 (.000317)	−.00147 (.000316)
Number of observations	16,709	16,679	15,905	16,636	16,473
Number of clusters	147/1,187	147/1,187	146/1,194	147/1,186	147/1,184
R-squared	0.808	0.808	0.810	0.808	0.808

Table 31: IV replication of Table 6 in Slave Trade Paper, including baseline controls, colonial controls for ethnicity-level, colonial population density. reliance on fishing and distance to Saharan city/route.

To replicate tables 9 and 10 of Nunn and Wantchekon (2011) using OLS, I executed the provided .do file in Stata and captured the results in tables 32 and 33. In Table 32, the regression for intergroup trust measures also includes the average slave export measure of respondents in the Afrobarometer survey that live in the same district, region, or village as the respondent. Furthermore, an ethnicity-based slave export measure is included in the regression as a baseline measure for each out of five trust variable. In Table 33, additionally to the same baseline measure, a location-based slave export measure is included in the OLS regression. This measure is the natural log of the number of slaves taken from the location where an individual is currently living (normalized by land area). Both OLS replications of these tables yield similar results to the ones in Nunn and Wantchekon (2011):

	Trust of relatives (1)	Trust of neighbors (2)	Within town (3)	Within district (4)	Within province (5)
Ethnicity-based slave export measure	−.0720	−.0704	−.102	−.120	−.0982
(baseline measure)	(.0194)	(.0191)	(.0282)	(.0268)	(.0294)
Average slave export measure amongst other			−.0366	−.0630	−.0908
ethnicities in the same location			(.0291)	(.0302)	(.0352)
Council trustworthiness fixed effects	Yes	Yes	No	No	No
Five public goods fixed effects	No	Yes	No	No	No
Number of observations	12,827	12,203	9,673	12,513	15,999
Number of clusters	146/1,172	145/1,130	147/725	147/737	147/1,127
R-squared	0.367	0.368	0.117	0.120	0.117

Table 32: OLS replication of Table 9 in Slave Trade Paper, including baseline controls, colonial controls for etnicity-level, and colonial population density.

	Trust of relatives (1)	Trust of neighbors (2)	Trust of local council (3)	Intra-group trust (4)	Inter-group trust (5)
Ethnicity-based slave export measure	−.155	−.182	−.0999	−.169	−.0895
(baseline measure)	(.0287)	(.0289)	(.0230)	(.0331)	(.0300)
Location-based slave export measure	−.0580	−.0406	−.0677	−.0385	−.0470
	(.015)	(.0189)	(.0175)	(.0223)	(.0239)
Number of observations	15,999	15,972	15,221	15,931	15,773
Number of clusters	146/269	146/269	145/272	146/269	146/269
R-squared	0.133	0.158	0.207	0.151	0.118

Table 33: OLS replication of Table 10 in Slave Trade Paper,including baseline controls, colonial controls for etnicity-level, and colonial population density.

D The Rise of Europe

	Whole sample, unweighted	Whole sample, weighted	Atlantic Western Europe	Non-Atlantic Western Europe	Eastern Europe	Asia
			Weighted by population			
Urbanization rate	0.0664	0.0991	0.801	0.101	0.0409	0.110
in 1300	(0.0523)	(0.0316)	(0.0282)	(0.0613)	(0.0327)	(0.00707)
Urbanization rate	.0.0764	0.103	0.0852	0.121	0.0394	0.111
in 1400	(0.0948)	(0.0360)	(0.0240)	(0.0997)	(0.0145)	(0.00527)
Urbanization rate	0.0834	0.106	0.101	0.114	0.0395	0.115
in 1500	(0.0764)	(0.0343)	(0.0533)	(.0676)	(0.0176)	(0.00707)
Urbanization rate	0.0963	0.117	0.136	0.140	0.0440	0.120
in 1600	(0.0759)	(0.0403)	(0.0763)	(0.0877)	(0.0275)	(0.00705)
Urbanization rate	0.107	0.112	0.145	0.131	0.0373	0.115
in 1700	(0.0847)	(0.0405)	(0.0683)	(0.0809)	(0.0216)	(0.00664)
Urbanization rate	0.141	0.102	0.198	0.169	0.0703	0.0894
in 1800	(0.0908)	0.0488	(0.0792)	(0.0752)	(0.0327)	(0.0141)
GDP per capita	627.539	608.29	721.46	850.73	506.94	575
in 1500	(159.25)	(117.95)	(31.07)	(217.13)	(78.15)	(35.36)
GDP per capita	740.731	630.49	916.31	908.22	578.30	576.79
in 1600	(225.58)	(144.24)	(149.32)	(167.26)	(112.27)	(35.27)
GDP per capita	862.115	662.23	1079.21	980.81	636.01	574.19
in 1700	(348.37)	(208.10)	(321.40)	(128.19)	(136.09)	(35.34)
GDP per capita	988.000	691.66	1321.95	1095.40	719.50	575.46
in 1820	(373.57)	(264.51)	(348.65)	(125.32)	(174.88)	(45.65)
Constraint on executive	1.667	1.732	1.75	1.990	1.462	
in 1500	(0.761)	(0.792)	(0.563)	(0.991)	(0.787)	
Constraint on executive	1.667	1.533	1.617	1.544	1.452	
in 1600	(1.007)	(0.836)	(1.238)	(0.586)	(0.793)	
Constraint on executive	1.833	1.515	1.830	1.414	1.298	
in 1700	(1.308)	(1.175)	(1.761)	(0.941)	(0.755)	
Constraint on executive	2.25	2.18	3.986	1.898	1.000	
in 1800	(1.824)	(1.830)	(1.793)	(1.776)	0.000	
Atlantic coastline-to-area 0.00570	0.00139	0.0118	0.00257	0.000	0.000	
	(0.0117)	(0.00647)	(0.0181)	(0.00524)	(0.000)	

Table 34: OLS replication of Table 1 in Rise of Europe paper: Descriptive Stats

	Panel, 1300-1850 (1)	Panel, 1000-1850 (2)	Panel, 1300-1850 (3)	Panel, 1000-1850 (4)	Panel, 1300-1850, unweighted (5)	Panel, 1300-1850, with Asia (6)	Panel, 1300-1850, without Britain (7)	Panel, 1300-1850 (8)	Panel, 1000-1850 (9)	Panel, 1300-1850, unweighted (10)
					Atlantic trade potential is measured by:					
				Atlantic trader dummy		Atlantic coastline-to-area				
					Panel A: Flexible specification					
p-value for Western Europe × year dummies,1600-1850	[0.00]	[0.00]	[0.45]	[0.09]	[0.80]	[0.00]	[0.12]	[0.09]	[0.01]	[0.78]
Atlantic trade potential × 1500			0.0158	0.0086	0.0550	0.0142	0.0177	0.4997	0.376	0.7464
			(0.0208)	(0.0190)	(0.0260)	(0.0218)	(0.0159)	(0.6831)	(0.6449)	(0.865)
Atlantic trade potential × 1600			0.0060	−0.0041	0.0495	0.0054	0.0085	0.2045	0.0297	0.9392
			(0.0230)	(0.0211)	(0.0280)	(0.0280)	(0.0175)	(0.6823)	(0.6414)	(0.9369)
Atlantic trade potential × 1700			0.0322	0.0222	0.0708	0.0316	0.024	1.811	1.638	2.01
			(0.0213)	(0.0192)	(0.0280)	(0.0257)	(0.0161)	(0.6296)	(0.5824)	(0.9369)
Atlantic trade potential × 1750			0.0323	0.0221	0.0734	0.0316	0.0226	2.164	1.988	2.602
			(0.0205)	0.0184	(0.0280)	(0.0247)	(0.0155)	(0.6191)	(0.5705)	(0.9369)
Atlantic trade potential × 1800			0.0475	0.0375	0.1115	0.0469	0.0276	3.303	3.124	3.764
			(0.0193)	0.0171	(0.0280)	(0.0233)	(0.0147)	(0.565)	(0.5083)	(0.9369)
Atlantic trade potential × 1850			0.0848	0.0755	0.1146	0.0842	0.0426	5.052	4.881	4.672
			(0.0180)	(0.0157)	(0.0280)	(0.0217)	(0.0138)	(0.5103)	(0.4439)	(0.9369)
R-squared	0.87	0.85	0.890	0.871	0.817	0.844	0.925	0.920	0.827	
Number of observations	192	240	192	240	192	208	184	192	240	192
					Panel B: Structured Specification					
p-value for Western Europe × year dummies, 1600 - 1850	[0.000]	[0.000]	[0.35]	[0.06]	[0.83]	[0.00]	[0.11]	[0.16]	[0.02]	[0.81]
Atlantic trade potential × volume of Atlantic trade		0.011	0.0083	0.016	0.011	0.005	0.75	0.65	0.62	
		(0.0024)	(0.0020)	(0.0034)	(0.0029)	(0.0018)	(0.07)	(0.06)	(0.11)	
R-squared	0.87	0.85	0.88	0.86	0.81	0.84	0.92	0.92	0.90	0.82
Number of observations	192	240	192	240	192	208	184	192	240	192

Table 35: OLS replication of Table 2 in Rise of Europe paper: Atlantic Trade and Urbanization.
Dependent variable is country-level urbanization

	Panel, 1500-1820 (1)	Panel, 1500-1870 (2)	Panel, 1500-1820 (3)	Panel, 1500-1870 (4)	Panel, 1500-1820, unweighted (5)	Panel, 1500-1820, with Asia (6)	Panel, 1500-1820, without Britain (7)	Panel, 1500-1820 (8)	Panel, 1500-1870 (9)	Panel, 1500-1820, unweighted (10)
					Atlantic trade potential is measured by:					
				Atlantic trader dummy		Atlantic coastline-to-area				
					Panel A: Flexible specification					
p-value for Western Europe × year dummies,1600-1820 or -1870	[0.44]	[0.05]	[0.92]	[0.23]	[0.17]	[0.01]	[0.89]	[0.97]	[0.58]	[0.31]
Atlantic trade potential × 1600			0.14	0.15	0.16	0.14	0.13	4.43	4.46	3.42
			(0.07)	(0.11)	(0.07)	(0.13)	(0.07)	(2.42)	(3.61)	(2.21)
Atlantic trade potential × 1700			0.18	0.19	0.21	0.18	0.14	8.84	8.80	6.32
			(0.07)	(0.10)	(0.07)	(0.12)	(0.06)	(2.27)	(3.40)	(2.21)
Atlantic trade potential × 1820			0.27	0.27	0.18	0.27	0.20	12.03	11.89	8.06
			(0.06)	(0.10)	(0.07)	(0.11)	(0.06)	(2.10)	(3.14)	(2.21)
Atlantic trade potential × 1870				0.22					15.84	
				(0.09)					(2.93)	
R-squared	0.94	0.94	0.96	0.95	0.96	0.92	0.96	0.96	0.96	0.96
Number of observations	96	120	96	120	96	104	92	96	120	96
					Panel B: Structured Specification					
p-value for Western Europe × year dummies, 1600-1820 or -1870	[0.44]	[0.05]	[0.92]	[0.48]	[0.14]	[0.01]	[0.88]	[0.99]	[0.54]	[0.23]
Atlantic trade potential × volume of Atlantic trade			0.069	0.040	0.047	0.069	0.051	3.21	3.18	2.22
			(0.016)	(0.017)	(0.018)	(0.028)	(0.015)	(0.53)	(0.50)	(0.58)
R-squared	0.94	0.94	0.96	0.95	0.96	0.92	0.96	0.96	0.96	0.96
Number of observations	96	120	96	120	96	104	92	96	120	96

Table 36: OLS replication of Table 3 in Rise of Europe paper: Atlantic Trade and GDP per capita.
Dependent variable is country-level log GDP per capita

	Balanced panel, 1300-1850, weighted (1)	Balanced panel, 1300-1850, unweighted (2)	Balanced panel, 1300-1850, weighted (3)	Balanced panel, 1300-1850, unweighted (4)	Balanced panel, 1300-1850, weighted, without London and Amsterdam (5)	Balanced panel, 1300-1850, weighted, with full set of country × year interactions (6)	Balanced panel, weighted, 1300-1850, weighted with Asia (7)
	Atlantic	port	Potential Atlantic Port				Atlantic port
p-value for Western Europe × year dummies,1600-1850	[0.34]	[0.05]	[0.30]	[0.16]	[0.28]	[0.30]	[0.41]
Atlantic port × 1500	−0.04 (0.19)	−0.05 (0.20)	0.027 (0.17)	0.048 (0.16)	−0.008 (0.20)	−0.072 (0.20)	−0.03 (0.20)
Atlantic port × 1600	0.36 (0.16)	0.46 (0.20)	0.41 (0.14)	0.43 (0.16)	0.41 (0.17)	0.36 (0.17)	0.36 (0.16)
Atlantic port × 1700	0.71 (0.14)	0.62 (0.20)	0.76 (0.13)	0.76 (0.16)	0.297 (0.17)	0.47 (0.17)	0.71 (0.15)
Atlantic port × 1750	0.70 (0.14)	0.71 (0.20)	0.79 (0.13)	0.89 (0.16)	0.26 (0.16)	0.46 (0.16)	0.70 (0.15)
Atlantic port × 1800	0.79 (0.14)	0.92 (0.20)	0.95 (0.12)	1.10 (0.16)	0.32 (0.15)	0.57 (0.15)	0.80 (0.14)
Atlantic port × 1850	1.09 (0.13)	1.00 (0.20)	1.19 (0.12)	1.23 (0.16)	0.48 (0.14)	0.46 (0.14)	1.09 (0.14)
p-value for Mediterranean port × year dummies, 1500-1850							
R-squared	0.92	0.79	0.92	0.80	0.89	0.95	0.94
Number of observations	1544	1544	1544	1544	1528	1544	1624
Panel B: Structured Specification							
p-value for Western Europe × year dummies, 1600-1850	[0.23]	[0.04]	[0.23]	[0.10]	[0.31]	[0.33]	[0.30]
Volume of Atlantic trade × Atlantic port	0.17 (0.02)	0.16 (0.02)	0.17 (0.017)	0.16 (0.024)	0.065 (0.019)	0.078 (0.018)	0.17 (0.018)
p-value for Mediterranean port × year dummies, 1500-1850							
R-squared	0.92	0.79	0.92	0.80	0.89	0.95	0.94
Number of observations	1544	1544	1544	1544	1528	1544	1624

Table 37: OLS replication of Table 5 in Rise of Europe paper: Growth of Atlantic Ports

	Panel, 1300-1850 (1)	Panel, 1300-1850 (2)	Panel, 1300-1850 (3)	Panel, 1300-1850, controlling for religion (4)	Panel, 1300 to 1850, controlling for wars (5)	Panel, 1300 to 1850, controlling for Roman heritage (6)	Panel, 1300 to 1850, controlling for latitude (7)	Panel, 1300 to 1850, using Atlantic coastline-to-area measure of potential for Atlantic trade (8)	Panel, 1300 to 1850, using Atlantic coastline-to-area measure of potential for Atlantic trade (9)
p-value for Western Europe × year dummies,1600-1850	[0.00]	[0.35]	[0.00]	[0.00]	[0.00]	[0.26]	[0.00]	[0.00]	[0.00]
Atlantic trade potential × 1500		−0.42 (0.47)						−20.83 (22.94)	
Atlantic trade potential × 1600		−0.14 (0.52)						10.94 (22.91)	
Atlantic trade potential × 1700		0.29 (0.48)						62.12 (21.14)	
Atlantic trade potential × 1750		0.32 (0.46)						81.45 (20.78)	
Atlantic trade potential × 1800		2.07 (0.44)						79.81 (18.97)	
Atlantic trade potential × 1850		2.96 (0.41)						72.25 (17.13)	
Atlantic trade potential × volume of Atlantic trade			0.42 (0.06)	0.45 (0.06)	0.43 (0.06)	0.39 (0.06)	0.43 (0.06)		12.99 (2.31)
p-value for Protestant × year effect				[0.00]					
Wars per year in preceding century					−0.034 (0.20)				
p-value for Roman heritage × year						[0.05]			
p-value for latitude × year							[0.49]		
R-squared	0.75	0.85	0.81	0.84	0.81	0.82	0.81	0.81	0.79
Number of observations	192	192	192	192	176	192	192	192	192

Table 38: OLS replication of Table 6 in Rise of Europe paper: Atlantic Trade and Institutions