Natural Resources: A Blessing for Everyone ?

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Work in Progress

Abstract

This paper studies the behavior of cross-country growth rates with respect to resource abundance and dependence. We reject the linear model commonly used for growth regressions in favor of a multiple regime alternative. Using a proper sample splitting methodology, we show that countries exhibit different behavior with respect to natural resources depending on their initial development. In high-income economies, natural resources play a minor role in explaining the differences in national growth rates. In low-income economies, abundance seems to be a blessing, but dependence hampers growth possibilities.

Keywords: Natural resource curse; Economic growth; Growth regressions; Multiple growth regimes

JEL Codes: O11; O13; Q0.

1 Introduction

Following the seminal work of Sachs & Warner (1995), a huge literature has developed on the so-called resource curse. The latter refers to the paradox that resource-abundant countries experience lower long run economic growth than do resource-poor countries.

Five major transmission channels have been identified in the literature to explain the resource curse. The most popular is the "Dutch disease", which has been widely documented in the literature (see for example Corden, 1984; Krugman, 1987; Bruno & Sachs, 1982; Torvik, 2001;

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Matsen & Torvik, 2005). This refers to the deterioration in the terms of trade that results from the real exchange-rate appreciation following a resource boom. This shift in the terms of trade has a negative impact on non-resource sectors. A second channel is the potential negative effect of natural resources on education. Following Gylfason (2001) and Sachs & Warner (1999), the abundance of natural resources increases the agent's opportunity cost of human-capital investment. The third channel refers to institutional quality. Resources may induce rent-seeking behaviors, which reduce institutional quality (a major determinant of economic growth) through corruption or armed conflict (see Jensen & Wantchekon, 2004; Robinson *et al.* , 2006; Adani *et al.* , 2014). Natural resources may also crowd out physical-capital investment (Sachs & Warner, 1995). A resource boom implies a shift in the distribution of production factors, from the secondary and tertiary sectors to the primary sector. As the manufacturing and tertiary sectors are more likely to exhibit increasing returns to scale and positive externalities than the primary sector, this shift will reduce productivity and the profitability of investment. Last, the volatility in resource prices could increase macroeconomic instability, which in turn inhibits growth (Van der Ploeg & Poelhekke, 2009).

Alongside this literature on the transmission channels of the resource curse, there are great debates over the evidences for the resource curse. Those debate are mainly driven by the fact that resource rich countries have diverse experiences. While Nigeria's oil revenues increased considerably between 1966 and 2010, its real GDP per capita in constant PPP has been multiplied by around 2.2.[1] Symmetrically, Botswana was one of the poorest country in the world while gaining independence in 1966. It has experienced one of the largest growth rate over the four last decades thanks to its diamonds deposits. Its GDP per capita in constant PPP has been multiplied by around 14.8.[2] Nowadays, it is one of the richest African countries and has left the least developed economies group in 1994.[3] Together with Botswana, Indonesia, Malaysia, and Thailand are often cited as developing resource rich economies that achieve a long-term investment ratio larger than one GDP quarter. While some suggests that those countries have escaped from the resource curse, it appears that they perform less well relative to their neighbors endowed with fewer raw materials: Hong-Kong, Singapore and South-Korea (Van der Ploeg, 2011).The World Bank estimates (Table 1) tend to show that the subsoil asset and natural capital shares are higher in low and middle income economies than in developed ones. Symmetrically, the intangible capital share increases with the level of development.

[1]Its GDP per capita in constant PPP was 2240 $ in 1966, 5030 $ in 2010 (source: PWT9.0).

[2]Its GDP per capita in constant PPP was 872 $ in 1966, 12871 $ in 2010 (source: PWT9.0).

[3]Since its creation in 1971, five countries have left the least developed economies group: Botswana (1994), Capo Verde (2007), Maldives (2011), Mauritania and Samoa (2014). Nowadays, the group still includes 48 countries.

Table 1: Total wealth and subcomponent in 2005

Income group	Subsoil asset share	Natural capital share	Produced capital share	Intangible capital share
Low-income	6.02%	35.50%	11.31%	53.18%
Middle-income	7.80%	20.57%	19.09%	60.32%
High-income	1.09%	2.50%	17.03%	80.47%
World	2.41%	6.16%	17.32%	72.18%

Notes: Estimates in 2005 U.S. dollars per capita. Source: Own calculation based on World Bank 2011.

In order to investigate the resource curse, growth regressions are often used. The seminal paper by Sachs & Warner (1995) uses growth regressions to show that the natural resource share of exports is negatively associated with economic development. They extend their work in order to show that there is little evidence that the curse is explained by omitted geographical variables (Sachs & Warner, 2001). Atkinson & Hamilton (2003) rely on a closer methodology in order to give evidence that the resource curse may be explained by the incapacity of governments to manage big resource revenues in a sustainable way. Papyrakis & Gerlagh (2004) use growth regressions in order to study the resource curse transmission channels. Alongside these positive analysis, there are also some normative works relying on growth regressions. Among others, Sala-i Martin & Subramanian (2008) rely on growth regressions in order to suggest that resource-rich economies (and Nigeria more precisely) should directly distribute the oil revenues to the population.

The use of growth regressions in this literature often comes with two major problems, as highlighted by Brunnschweiler & Bulte (2008): *i)* natural resource exports over GDP capture resource dependence more than resource abundance, and their use as a proxy for abundance may lead to the misinterpretation of the regression results (see Figure 1); *ii)* introducing resource dependence and institutional variables in growth regressions may produce endogeneity biases: resource dependence is related to economic choices that simultaneously affect growth. Natural resources may also reduce institutional quality (as in the third channel above), which in turn affects resource dependence through the economic policies that depend on institutions. They address this endogeneity problem via Three Stage Least Squares (3SLS) regressions using historical openness and the presidential regime in 1970s as instruments for resource dependence, while institutional quality is instrumented by latitude.[4] They conclude that resource abundance has a positive effect on economic growth while resource dependence has no effect: the resource curse may then be a red herring.

[4]Other popular instruments are also used in robustness check regressions. The results remain unchanged.

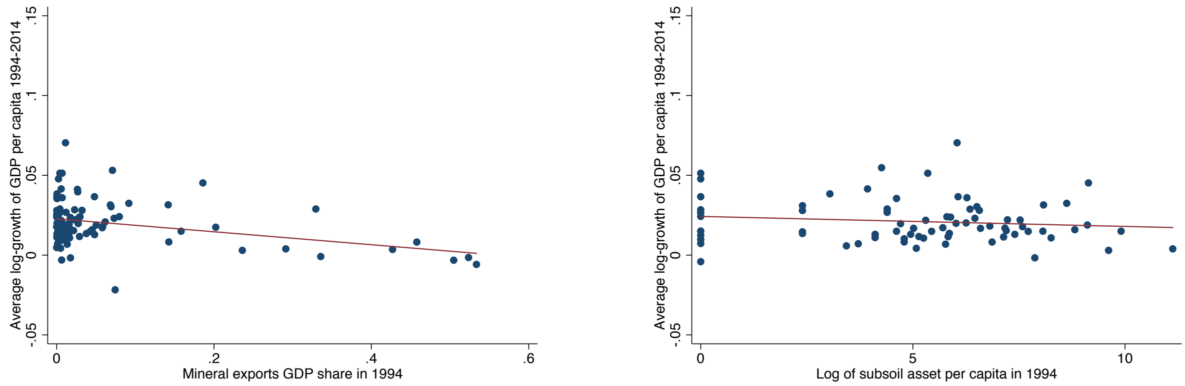

Figure 1: Economic growth, resource dependence and resource abundance

Brunnschweiler & Bulte (2008) introduce regional dummies to pick up the differences in average economic growth across regions, conditional on the other explanatory variables. However, this choice of regions needs to be discussed and justified, as countries in the same region are very heterogeneous regarding climate, geology, culture, politics and economics. Using the same dataset, Clootens & Kirat (2017) show that the impact of resource dependence on growth turns to be strongly negative and significant when we omit the regional dummies.[5] Moreover, the way in which Brunnschweiler & Bulte (2008) take into account regional heterogeneities constrains the model parameters (apart from the constant) to be the same across regions. Durlauf & Johnson (1995) show that the linear model commonly used to study growth behavior may be misspecified and they argue for a multiple regime alternative.

Clootens & Kirat (2017) relax this linearity assumption and allow all estimated parameters to vary across regions. They split the sample into two distinct regions, Northern and Southern countries.[6] As this split is subjective, they also investigate OECD versus non-OECD countries. They obtain the following results[7]: southern (non-OECD) and northern (OECD) economies do not behave in the same way with respect to resource dependence: resource dependence cut down growth in low-income economies (see also Figure 2 and 3).

[5]Results from this paper are reported in Appendix A.3.

[6]This split is carried out using the areas in Brunnschweiler & Bulte (2008). Northern countries include North-American, European and Central-Asian countries. They do not investigate African and Middle Eastern countries versus the rest of the world separately as the subsample of African and Middle Eastern countries contains too few observations.

[7]Those results are reported in Appendix A.3.

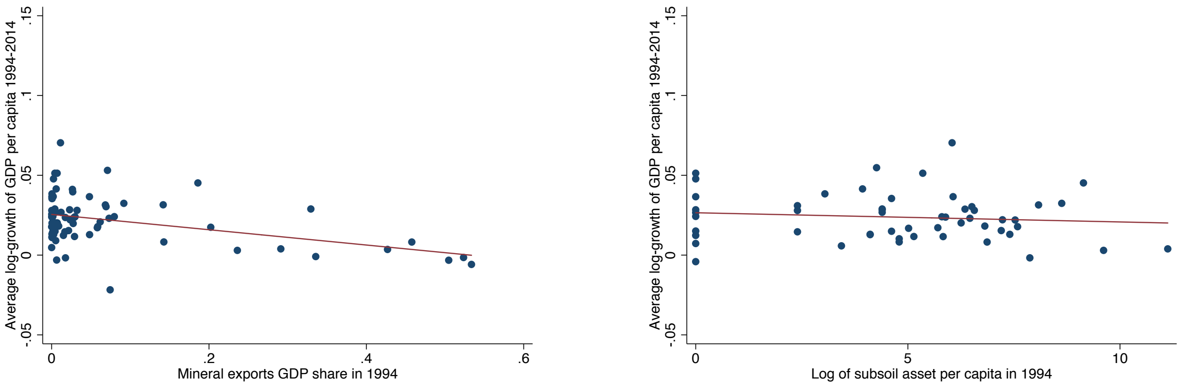

Figure 2: Economic growth, resource dependence and resource abundance in non-OECD countries

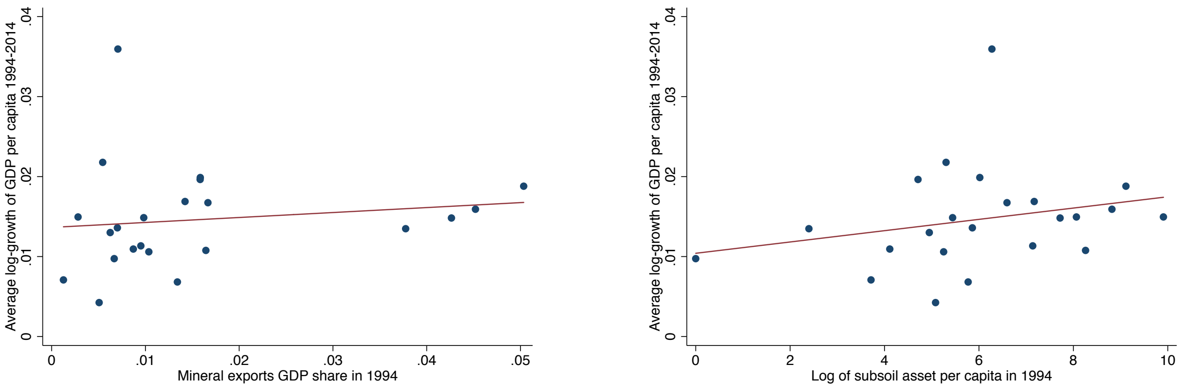

Figure 3: Economic growth, resource dependence and resource abundance in OECD countries

The sample splitting in Clootens & Kirat (2017) is subjective, and calls for a proper sample splitting methodology. In this chapter we propose to use Hansen (2000)'s sample splitting methodology. It allow to test for a threshold effect and estimates that threshold endogenously. Using two different datasets, we find that there exists a value of initial GDP that splits the sample into two subsamples. We estimate the threshold and run regressions on our subsamples. Using this methodology confirms the previously obtained results: resource dependence slows down growth in low-income economies while resource abundance seems to be a blessing.

The rest of the chapter is organized as follows. Section 2 describes our two datasets. Section 3 presents the estimation strategy. Section 4 presents our results and their interpretations. Section 5 provides the usual test and a robustness check while section 6 concludes.

2 Data

In the following, the econometric work will be performed on two separate datasets.[8] One is the dataset used by Brunnschweiler & Bulte (2008) (B&B dataset hereafter) and covers the 1970-2000 period. The second one (our own dataset) covers the period 1980-2014 and includes new countries.[9]

In B&B dataset, *Growth* refers to the average log-growth of real (PPP in current \$) GDP per capita between 1970 and 2000. $gdp_{t=0}$ represents the real (PPP in current \$) GDP per capita in 1970. Resource dependence (RD) represents the GDP share of mineral exports (sum of mineral fuels, ores and metal exports[10]) averaged over 1970-1989. Resource abundance (RA) is measured as the log of subsoil asset in \$ per capita in 1994.[11] It includes exhaustively bauxite, copper, hard coal, iron, lead, lignite, natural gas, nickel, oil, phosphate, silver, tin and zinc. $Inst$ captures the effectiveness of contract enforcement, police and the courts, and likelihood of crime and violence in 1996. $pres_{t=0}$ is a dummy variable coded 1 if the regime is presidential, 0 if parliamentary. The first entry in 1970s is retained. Trade openness (*open*) is the (nominal) GDP shares of imports plus exports averaged over 1950s and 1960s.

In our dataset, *Growth* refers to the average log-growth of real (PPP in constant \$) GDP per capita between 1970 and 2000. The PWT 9.0 provide 5 estimations of GDP. We use the real GDP calculated using national-accounts growth rates, as recommended for growth regressions by Feenstra *et al.* (2015).[12] We also follow Feenstra *et al.* (2015)'s recommendation when we choose our initial GDP variable. We thus consider the real GDP in current PPP in 1980. Indeed, this variable limits the bias that may be introduced by the "constant PPP correction" and is best suited to measure initial GDP. Concerning RA, we use the log of subsoil asset per capita in \$ in 1994 plus one. We thus consider countries with no mineral asset in our regressions. Adding one to the subsoil asset is not so distortive since non-zero values for subsoil asset are quite elevated. Our RD variable is the average GDP share of mineral exports (defined as in the B&B dataset) over the 1980-2014 period. Our $Inst$ also captures the effectiveness of contract enforcement, police and the courts, and likelihood of crime and violence, but has been averaged

[8] Sources of data are provided in appendix A.1.

[9] We reproduce systematically our work on Brunnschweiler & Bulte (2008) database in order to check whether the results are robust and not driven by our own dataset. Moreover, a robustness check has been done using updated data from PWT 9.0 on the period 1970-2000.

[10] Fuels represents commodities in Standard International Trade Classification (SITC) 3 while ores and metal comprises goods in SITC 27, 28, and 68.

[11] Taking the log replaces 0 by missing values. One may argue that it can cause a distortion of obtained results.

[12] PWT 9.0 also includes GDP in constant PPP, in current PPP, estimated from both the demand and supply sides.

over the period in order to give a better representation of the "average" institutional quality during the considered period. For $pres_{t=0}$ we retained the first entry in 1980s. Finally, our trade openness variable is the sum of real (current PPP) GDP shares of imports and exports averaged over the 1970s. We do not consider previous periods in order to obtain a maximum of observations in the database.

Finally, *latitude* is common to both datasets. It is the latitude in absolute value of a country (its capital) divided by 90 in order to be scaled between 0 and 1.

Table 2: Descriptive statistics

	B&B data				Own data			
	Mean	S.D	Min.	Max.	Mean	S.D	Min.	Max.
$growth(\%)$	5.822	1.789	-0.304	9.807	1.603	1.470	-1.573	6.264
RA	5.793	1.861	2.303	9.908	5.071	2.765	0.000	11.126
RD	0.058	0.091	0.000	0.437	0.064	0.089	0.000	0.489
$gdp_{t=0}$	7.077	0.915	5.493	8.517	8.481	1.160	6.273	10.815
$Inst$	0.391	1.046	-1.270	2.100	0.093	1.065	-1.563	1.953
$pres_{t=0}$	0.552	0.502	0.000	1.000	0.627	0.487	0.000	1.000
$open$	0.426	0.240	0.062	1.194	0.345	0.262	0.020	1.298
$latitude$	0.306	0.199	0.010	0.710	0.280	0.196	0.011	0.711

The list of countries is reported in Appendix A.2. Each dataset contains respectively 58 and 75 countries.

Table 2 presents descriptive statistics for both datasets. The first part covers B&B dataset while the second covers our own dataset. In general, there are few variations in our two datasets but some variables exhibit important differences in both subsamples. Notably, *growth* is quite different. This difference is mainly due to the method of calculation of the variable. Thus, our growth variable is able to take into account the variations of PPP across time following recent Penn World Table progress.[13] The second variable which exhibits a difference between the two subsample is the institutional one. The difference may be due to the inclusion of new countries in our dataset.

[13]The distinction between several GDP variables has been introduced in PWT 9.0. Conversion table to previous versions exists.

3 Estimation strategy

3.1 The threshold model

The main equation in the linear model considered by Brunnschweiler & Bulte (2008) is very close to the following:[14]

$$Growth_i = \beta_0 + \beta_1 RD_i + \beta_2 RA_i + \beta_3 Inst_i + \beta_4 gdp_{t=0,i} + \varepsilon_i \tag{1}$$

This regression can also be written as follows:

$$Growth_i = \Psi X_i + \varepsilon_i \tag{2}$$

where $\Psi = (\beta_0, \beta_1, \beta_2, \beta_3, \beta_4)$ and $X_i = (1, RD, RA, Inst, gdp_{t=0})'$. We look for a possible nonlinear effect induced by real GDP per capita in 1970. The choice of the transition variable among explanatory variables when we implement threshold models is a key issue. In many papers, the choice is based on economic theory. We rely on the literature on convergence clubs to consider here initial real GDP per capita as the threshold variable. The idea is to show that there are different trajectories in growth, depending on the initial level of GDP. We believe that such differences may be measured by the asymmetry of the GDP long-run growth relative to initial GDP.[15] Hansen (2000) uses initial GDP as the threshold variable in growth regression in order to illustrate its methodology. This idea is inspired by Durlauf & Johnson (1995). Clootens & Kirat (2017) give some proofs that countries react differently to an increase in resource dependence depending on their initial GDP. Thus, we use the following threshold regression model:

$$Growth_i = \begin{cases} \Psi^1 X_i + \varepsilon_i & if \quad gdp_{t=0,i} \leq q \\ \Psi^2 X_i + \varepsilon_i & if \quad gdp_{t=0,i} > q \end{cases} \tag{3}$$

where $\Psi^1 = (\beta_0^1, \beta_1^1, \beta_2^1, \beta_3^1, \beta_4^1)$ and $\Psi^2 = (\beta_0^2, \beta_1^2, \beta_2^2, \beta_3^2, \beta_4^2)$. The threshold parameter q is considered to be unknown. It is convenient to rewrite (3) as follows:

$$Growth_i = \Psi^2 X_i + \lambda X_i \mathbb{1}_{gdp_{t=0,i} \leq q} + \varepsilon_i \tag{4}$$

[14] We omit the regional dummies.

[15] In other papers, the threshold variable is selected using a test procedure based on linearity tests. The procedure applies first linearity tests for each of the explanatory variables. Then, the threshold variable is selected as the one with the lowest risk of error when linearity is rejected. This statistical approach does not have theoretical economic foundations. It presents the disadvantage of selecting a threshold variable which is different from the variable of interest (related to economic theory). For this reason many authors hold our approach.

where $\lambda = \Psi^1 - \Psi^2$. We want to estimate Ψ^1, Ψ^2 and q if the null hypothesis of linearity is rejected, i.e. $H_0: \ \lambda = 0$ in equation (4).

We first examine the null hypothesis of linearity in equation (4), $H_0: \ \lambda = 0$. Without an *a priori* fixed value of q in regression (4), it is not easy to make any statistical inference regarding λ. In this case q is a nuisance parameter which is not identified under the null hypothesis. To avoid this problem, Hansen (1996) developed a simulation technique producing a p-value statistic for the inference of λ. His approach does not require fixing an *a priori* value of q and allows for possible heteroskedasticity in (4). The computation method of the threshold estimate $\widehat{q}$ uses the concentrated sum of squared errors function from (4):

$$S(q) = \sum_{i=1}^{N} \left(Growth_i - \widehat{\Psi^2}(q) X_i - \widehat{\lambda}(q) X_i(q) \right)^2 \tag{5}$$

and the threshold estimate $\widehat{q}$ is the value that minimizes $S(q)$:

$$\widehat{q} = \underset{q \epsilon \Gamma}{\arg\min} S(q) \tag{6}$$

where Γ is a bounded set of elements of $\{gdp_{t=0,i}, i = 1, ..., N\}$ and can be approximated by a grid (see Hansen, 2000). Finally, the slope estimates in the threshold model (3) can be computed via $\widehat{\Psi^2}(\widehat{q})$ and $\widehat{\lambda}(\widehat{q})$. Hansen (2000) also developed asymptotic distribution theory for the threshold estimate $\widehat{q}$, and proposed asymptotic confidence intervals by inverting the likelihood-ratio statistic. His approach again allows for possible heteroskedasticity in (4).

3.2 Dealing with endogeneity

Why one may want to apply the threshold regression on equation (1), our estimation may suffer from an endogeneity bias. Indeed, Brunnschweiler & Bulte (2008) identify several source of endogeneity that may affect the model.

Firstly, the institutional quality might be not invariant with respect to some of the deep economic variables. Thus, the coefficient on institutions in growth regression may be biased due to some omitted variables.

Secondly, *RD* is not a proper explanatory variable in growth regressions because its denominator is the GDP. Thus, it is likely to be correlated with various variables that also determines economic growth. Considering resource dependence as exogenous may thus lead to biased outcomes.

It has been well established that resources may be a curse for countries with a low institutional level, and a blessing for countries with good institutions. Nowadays, the consensus goes one step further and argues that the institutional quality is not invariant with respect to resource endowments. In order to properly account for the impact of both $Inst$ and RD in growth regression, an instrumental variable procedure (instrumenting for $Inst$ in a first step and RD in a second step) should be undertaken.

Another concern rely on the exogeneity of the resource abundance suggested by Brunnschweiler & Bulte (2008). Indeed, exploration and evaluation of resource stock is a technological intensive process which is not independent from countries' technological levels. Nevertheless, thanks to their economic potential, mineral deposits have been well explored and estimated by large multinational firms regardless of local conditions. While the resource abundance variable is not exempt from criticism[16], we believe that it constitutes an improvement with respect to the standard measure popularized by Sachs & Warner (1995).

Since endogeneity is suspected in equation (1) , $E(Inst \times \varepsilon) \neq 0$, the OLS estimator is not convergent. RD is also endogenous, and $Inst$ is a determinant of RD that may suffer from endogeneity, a good instrument z for institutional quality is such that $E(z \times \varepsilon) = 0$ and $E(z \times \mu) = 0$, where μ is the residual in the regression of RD on its determinant. Usually the literature uses mainly three alternative instruments in order to correct for the endogeneity bias induced by institutions: latitude, the fraction of population speaking a western European language (Hall & Jones, 1999) and the log of settler mortality (Acemoglu *et al.* , 2001).

Latitude and the fraction of population speaking a western language are measures of the extent to which an economy has been influenced by Western Europe, which is the first area which has implemented institutions favorable to production. Nevertheless, these variables are not impacted by current economic performance.[17]

As shown by Acemoglu *et al.* (2001) settler mortality is also a good instrument for institutions. Indeed, there were various types of colonization ranked from "extractive states" to

[16] Notably, Bohn & Deacon (2000) remark that economic policies may affect the present value of rents. Van der Ploeg & Poelhekke (2010) are also suspicious concerning the exogeneity of the abundance variable. Since the results obtained by Brunnschweiler & Bulte (2008) are robust to the use of different abundance variables (some of them proposed in the critical paper by Van der Ploeg & Poelhekke, 2010) we do not enter into this debate in the present work.

[17] This is especially true for latitude while economic development may affect the current percentage of English speaking people. Nevertheless, this difficulty may be avoided using the proportion of English speaking people in 1970.

"neo-europes" (Crosby, 2004). The feasibility of settlements has affected the colonization strategies such that "neo-europes" appeared where settler mortality was low. Since past institutions is a major determinant of current institutional quality, settler mortality seems to be a good instrument for institutions. In this chapter, latitude is used to correct the endogeneity bias because it is likely that mineral abundance promoted the establishment of extractive states.

Following Brunnschweiler & Bulte (2008), two perspectives on institutions may be distinguished. On the one hand, institutions may be seen as persistent constitutional variables (presidential vs parliamentary regimes, electoral rules...). Indeed, institutions may refer to "deep and durable" characteristics of a society (Glaeser *et al.* , 2004). On the other hand, institutions may also refer to the policy outcome in property right enforcement, fight against corruption and so on (Rodrik *et al.* , 2004). As previously explained, our variable $Inst$ refers to the second view, and may suffer from endogeneity while used in our second step estimation. Hence its instrumentation in a first step is necessary.

Deep and durable institutions may be used to instrument for resource dependence. Brunnschweiler & Bulte (2008) use a dummy variable (1 if the country is under a presidential regime in 1970s, 0 otherwise) as a proxy for institution. Indeed presidentialism is often associated with public expenditures biased in favor of private interest (including the primary sector) because the decision maker doesn't rely on a stable majority. They show that this variable is exogenous. They also suggest to instrument RD using past trade openness and show that it constitutes an exogenous instrument.[18]

Since the threshold estimation may be biased through endogeneity, we should use the corrected RD and $Inst$ variables to test for the threshold.

4 Results

We first perform the threshold test proposed by Hansen (2000) on an instrumented version of equation (1):

$$growth_i = \beta_0 + \beta_1 \widehat{RD}_i + \beta_2 RA_i + \beta_3 \widehat{Inst}_i + \beta_4 gdp_{t=0,i} + \varepsilon_i \tag{7}$$

where

$$\widehat{RD}_i = \widehat{\psi_0} + \widehat{\psi_1} pres_{t=0,i} + \widehat{\psi_2} RA + \widehat{\psi_3} \widehat{Inst}_i + \widehat{\psi_4} open_i + \widehat{\psi_5} gdp_{t=0,i} \tag{8}$$

[18]Using the predicted trade shares developed by Frankel & Romer (1999) as an instrument in order to consider the possible endogeneity of the openness measure does not affect their results.

and

$$\widehat{Inst_i} = \widehat{\phi_0} + \widehat{\phi_1} latitude + \widehat{\phi_2} RA + \widehat{\phi_3} gdp_{70,i} + \widehat{\phi_4} open_i + \widehat{\phi_5} pres_{t=0,i} \tag{9}$$

Thus, in equation (7), $\widehat{RD}$ and $\widehat{Inst}$ are the predicted values from instrumental regressions (8) and (9). Figure 4 represents the threshold test in both dataset. If the sequence exceeds the 95% critical value, linearity is rejected.

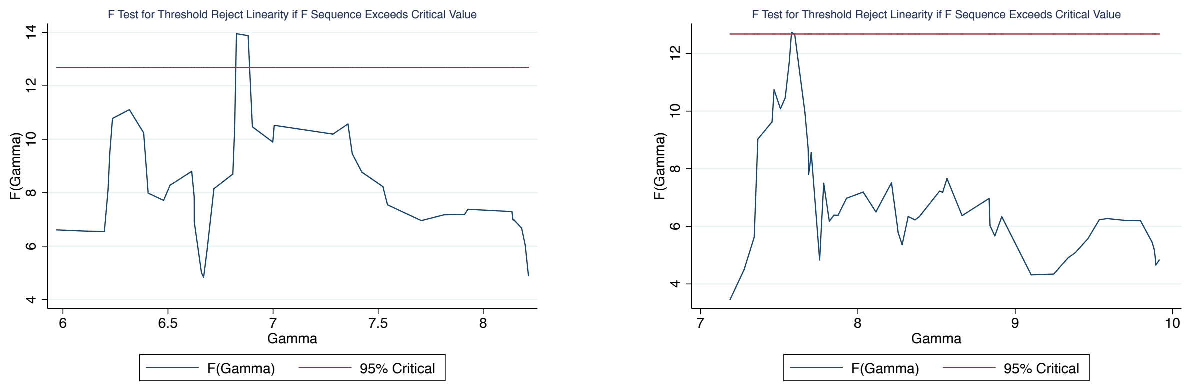

Figure 4: Threshold tests: the IV case

The test rejects the null hypothesis of linearity for both datasets. The reported p-values for the B&B and for our own dataset are respectively 0.022 and 0.049.[19] There exists a threshold value for initial GDP that splits our sample into two different subsamples, consistently with the findings of Clootens & Kirat (2017). Sample splitting estimation should be performed for both datasets.

Table 3: IV regressions by subgroups: B&B dataset

	Non-splitted	Splitted	
		$gdp_{t=0} \leq 6.88133$	$gdp_{t=0} > 6.88133$
Economic growth:			
RD	-9.714* (5.673)	-22.529** (9.659)	2.154 (3.896)
RA	0.508*** (0.160)	1.064*** (0.212)	-0.045 (0.091)
$Inst$	1.723*** (0.448)	1.293 (1.154)	1.097* (0.571)
$gdp_{t=0}$	-1.943*** (0.441)	-1.490* (0.840)	-0.880 (0.793)
$cons$	58	30	28
N	58	30	28
R^2	0.310	0.502	0.208

Notes: Robust standard errors in parentheses. *,** and *** refer respectively to the 10%, 5% and 1% significance levels. First steps results are reported in Appendix A.4.

[19]Bootstrapped p-values obtained with 5000 replications.

Table 4: IV regressions by subgroups: Own dataset

	Non-splitted	Splitted	
		$gdp_{t=0} \leq 7.46775$	$gdp_{t=0} > 7.46775$
Economic growth:			
RD	-6.438 (4.939)	-33.806*** (10.113)	0.365 (4.243)
RA	0.234** (0.103)	0.981*** (0.203)	0.026 (0.084)
$Inst$	0.886** (0.372)	-1.110 (1.576)	0.962** (0.361)
$gdp_{t=0}$	-1.085*** (0.305)	-3.305** (1.340)	-0.978*** (0.358)
$cons$	9.952*** (2.459)	22.634** (9.005)	9.739** (3.033)
N	75	16	59
R^2	0.209	0.749	0.153

Notes: Robust standard errors in parentheses. *,** and *** refer respectively to the 10%, 5% and 1% significance levels. First steps results are reported in Appendix A.4.

Table 3 and 4 confirm insights given in Clootens & Kirat (2017) on the necessity of sample splitting. Indeed, it appears that poor and rich countries (defined using Hansen (2000)'s methodology) do not behave in the same way with respect to natural resources. In low-income economies, resource dependence is a curse that cut down growth possibilities while resource abundance is still a blessing. In the B&B dataset, a one percentage point increase in the GDP share of mineral export leads to a decrease by 0.225 percentage point (0.338 in our dataset). Conversely, an one percent increase in subsoil asset is associated to a increase in growth of about 0.011 percentage point (0.009 in our dataset). The negative sign on initial GDP per capita captures a catch-up effect. A one percent increase in initial GDP leads to a decrease in the average growth rate by 0.014 percentage point (0.033 in our dataset). Institutions, once instrumented, seems to play a minor role in the growth of developing countries.

In high-income economies, growth is not determined by either dependence or abundance. Institutional quality seems to play a important role while we also find a catch-up effect (in our dataset only). Thus a one percent increase in initial GDP leads to a decrease in growth of about 0.097 percentage point.

The results on mineral dependence contradicts one of the main results given in Brunnschweiler & Bulte (2008): with sample splitting, dependence matters for the development of developing economies. Interpretation may go further. Usually, initial GDP per capita is introduced in growth regression in order to capture a catch-up effect. Here, this variable is also supposed to be the sample splitting variable. Thus, heterogeneity between sub-sample is taken into account. Implicitly, choosing this variable as the sample splitting one suppose that countries on a side of the threshold share common properties highly determined by development. Notably, it is believed that a country which has a high income per capita in 1970 (or 1980 depending on the dataset) is probably a country which exhibits a market-friendly environment: high level of educated people, developed financial markets, sufficient trade openness, non-observed institutional quality, high level of investment... While some of those variable may be biased through endogeneity, our approach takes the advantage to classify countries in two groups sharing common properties without any subjective choice, excepted that of the threshold variable.

We believe that our results help to understand the one that Brunnschweiler & Bulte (2008) obtain. Indeed, they introduce regional dummies in their regression, but the only significant coefficient is on Africa and Middle-East. Those dummies are introduced in order to control for geographical (cultural, climatic, natural, geological...) unobserved characteristics. Our results tend to confirm our insight that it captures something quite different. Indeed, the regional dummy they propose include a very large area with very different countries: South-Africa, Jordan, Tunisia and Togo (for example) seem to be sufficiently far away to not share common geographical characteristics. Since Africa is the poorest continent, we believe that the dummy captures unobserved differences strongly linked with initial development.

5 Usual Tests and Robustness Check

At this point, the accuracy of our instrumental procedure inspired from Brunnschweiler & Bulte (2008) may be questioned. We thus propose to present the usual test in order to justify the choice of the model.

We decide to use a 2sls methodology while Brunnschweiler & Bulte (2008) use 3sls. A 3sls methodology provokes an efficiency gain if: *i)* residuals of different steps are correlated ; *ii)* instruments are valid and strong.

Table 5: Correlation between residuals

	B&B dataset				Own dataset		
	$\hat{\varepsilon}$	$\hat{\mu}$	$\hat{\upsilon}$		$\hat{\varepsilon}$	$\hat{\mu}$	$\hat{\upsilon}$
$\hat{\varepsilon}$	1.000			$\hat{\varepsilon}$	1.000		
$\hat{\mu}$	-0.081 (0.545)	1.000		$\hat{\mu}$	0.159 (0.174)	1.000	
$\hat{\upsilon}$	0.493 (0.000)	-0.070 (0.604)	1.000	$\hat{\upsilon}$	0.471 (0.000)	-0.148 (0.206)	1.000

Notes: significance level in parenthesis

It appears from table 5 that for both subsamples, only $\hat{\varepsilon}$ and $\hat{v}$ are correlated. Since first stage regressions tend to show that our instruments are relatively strong, a 3sls procedure may be done.[20] Unfortunately, such a procedure is not compatible with threshold estimation since it will re-correct for endogeneity inside sub-samples. However, we can control for residuals correlations in each subsample estimating the model using a SURE methodology. This is not completely satisfactory because it does not correct for correlation residuals for the entire sample. Results on interest variables are unchanged (not reported).

Then, an over-identification test should be done. $Inst$ is just identified since we only use $latitude$ as an instrument. Nevertheless, we use two instruments for RD: $open$ and $pres_{70}$. We can then perform a Sargan-Hansen test of over-identifying restrictions.[21] Table 6 presents the results of the test: we cannot reject the null hypothesis that our instruments are uncorrelated with the error term. Validity of instruments is not rejected for our two datasets.

So far, endogeneity has been suspected in our data. Nevertheless, if the 2sls procedure has been applied while our data do not suffer from endogeneity, it implies an efficiency loss. In order to check the presence of endogeneity in our dataset, a Hausman test may be used.[22] This test can be performed using an augmented regressions. Table 6 reports the estimation of the coefficient $\gamma_{\hat{\mu}}$ and $\gamma_{\hat{v}}$ associated with $\hat{\mu}$ and $\hat{v}$ when introduced in (1).

Table 6: Over-identification test and Hausman test

	B&B dataset	Own dataset
Over-identification test		
Sargan-Hansen J-stat	0.102 ($\chi^2(1)$)	1.315 ($\chi^2(1)$)
p-value	0.7489	0.2515
Hausman test		
$\gamma_{\hat{\mu}}$ (s.e.)	8.875** (4.370)^a	0.046 (0.052)
$\gamma_{\hat{v}}$ (s.e.)	0.8133 (0.578)	0.003 (0.004)

Notes: Robust standard errors in parentheses. a. The p-value associated is 0.037; with non-robust standard errors it becomes 0.067; using bootstrap methods, it turns to be 0.051: one should be careful while rejecting exogeneity at the usual 5% threshold.

So far instruments seem to be valid but we cannot reject strongly the null hypothesis of exogeneity. If data do not suffer from endogeneity, a simple ols regression is more efficient than a 2sls regression. We believe that the suspicion for endogeneity is strong and sufficient to justify

[20] One may nonetheless argue that the 3sls procedure is useful in the presence of stronger instruments so that it will not an improvement here.

[21] See Baum *et al.* (2002) for its implementation in Stata with robust standard errors.

[22] A version of the Hausman test in the presence of robust standard errors has been implemented in Stata with ivreg2. See Baum *et al.* (2002) for details.

a 2sls procedure. Nevertheless, a robustness check using an ols methodology seems consistent. The results of threshold tests for an uninstrumented procedure are represented on figure 5:

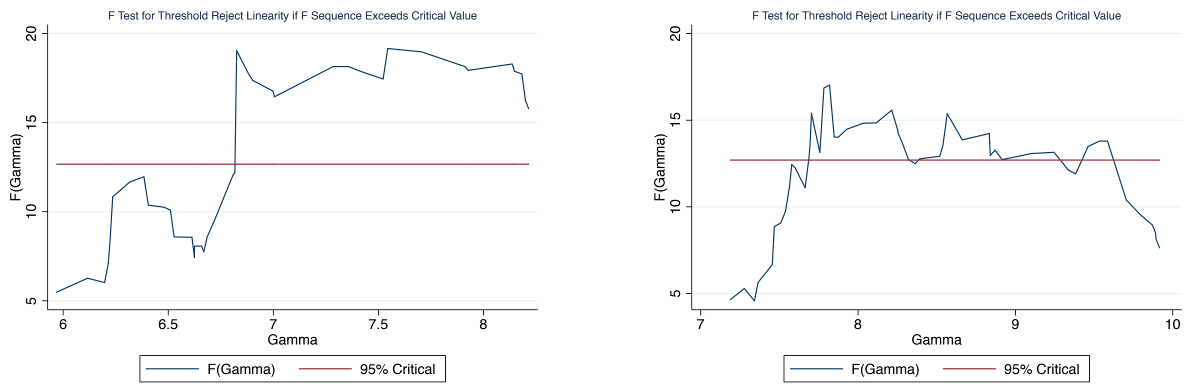

Figure 5: Threshold tests: the ols case

The threshold test argues for the rejection of the null hypothesis of linearity for both datasets.Table 7 and 8 present the results of threshold estimations.

Table 7: OLS regressions by subgroups: B&B dataset

	Non-splitted	Splitted	
		$gdp_{t=0} \leq 6.82567$	$gdp_{t=0} > 6.82567$
Economic growth:			
RD	-5.108 (4.538)	-10.522*** (3.252)	2.926** (1.385)
RA	0.396*** (0.144)	0.877*** (0.161)	-0.053 (0.070)
$Inst$	1.763*** (0.311)	2.399*** (0.626)	1.315*** (0.360)
$gdp_{t=0}$	-1.853*** (0.381)	-2.595*** (0.652)	-1.544* (0.756)
$cons$	16.247*** (2.452)	18.878*** (3.763)	16.983*** (5.426)
N	58	29	29
R^2	0.442	0.684	0.481

Notes: Robust standard errors in parentheses. *,** and *** refer respectively to the 10%, 5% and 1% significance levels.

Table 8: OLS regressions by subgroups: Own dataset

	Non-splitted	Splitted	
		$gdp_{t=0} \leq 7.78304$	$gdp_{t=0} > 7.78304$
Economic growth:			
RD	-2.820 (1.837)	-10.585** (4.044)	-0.209 (1.278)
RA	0.182** (0.069)	0.291* (0.140)	0.058 (0.050)
$Inst$	1.155*** (0.177)	2.425*** (0.505)	1.040*** (0.225)
$gdp_{t=0}$	-1.228*** (0.202)	-1.552** (0.576)	-1.226*** (0.318)
$cons$	11.166*** (1.620)	14.249*** (4.070)	11.861*** (2.948)
N	75	27	48
R^2	0.381	0.578	0.405

Notes: Robust standard errors in parentheses. *,** and *** refer respectively to the 10%, 5% and 1% significance levels.

In our dataset, results confirms those previously obtained: RD has a negative impact on growth while RA is a blessing for low-income economies. There here is still a catch-up effect in this group, while $Inst$ becomes significant, which seems quite obvious since OLS imply an efficiency gain with respect to IV in absence of endogeneity. Either natural resources abundance or dependence do not affect growth in developed economies.

Concerning the B&B dataset, results are similar for low-income economies. The case of high-income countries is more dubious. Indeed, the coefficient on resource dependence is strongly positive and significant. This result may be explained by endogeneity since the Hausman test presented in table 6 confirms that we can reject the null of linearity at the 5% threshold.

6 Conclusion

This chapter amends the work of Brunnschweiler & Bulte (2008) in order to improve the way they consider heterogeneities between countries. Notably, it uses the sample splitting methodology proposed by Hansen (2000) on the same dataset. One of their main result is affected: resource dependence negatively affect development, at least for low-income economies. We recognize that this result is not independent with the choice of the threshold variable. While our method allow to test for and to estimate the value of the threshold without any subjective consideration, the economist still have to choose the threshold variable. Initial GDP is highly correlated with human capital, current trade openness, financial development... Thus, one may argue that our results confirm the view developed by Van der Ploeg (2011) that market-friendly (i.e. high income) economies tend to answer differently than other economy to an increase in resource dependence.

This chapter strongly rely on the work of Brunnschweiler & Bulte (2008). Notably, we have chosen to use a model close to their model and to correct for the way they take into account heterogeneities between countries. Thus, we answer to some of Van der Ploeg & Poelhekke (2010)'s critics. Notably, it is believed that dividing the sample into subsamples on an initial development criterion allow us to take into account differences in the level of human capital, investment, financial markets development, and other missing variables strongly correlated with economic development. Also, the GDP growth variable considered here answers to Van der Ploeg & Poelhekke (2010) suspicion on constant GDP growth rate. However, further research should extend the present work notably considering Van der Ploeg & Poelhekke (2010) criticism on the instrumental variables choice and procedure.

A.1 Data sources

The following table describes data sources for each variable:

Table 9: Sources of variables

Source	Variables	Dataset
Penn World Table 6.1	$Growth$	B&B
	$open$	B&B
	$gdp_{t=0}$	B&B
Penn World Table 9.0	$Growth$	Own
	$open$	Own
	$gdp_{t=0}$	Own
World Development Indicators, The World Bank	RD	Both
The World Bank (1997)	RA	Both
Kaufmann *et al.* (2004)	$Inst$	Both
Beck *et al.* (2001) and Persson & Tabellini (2004)	Both $pres_{t=0}$	Both
La Porta *et al.* (1999)	$latitude$	Both

We would like to thank Christa N. Brunnschweiler and Erwin H. Bulte to provide their entire dataset on Christa Brunnschweiler's personal website.

A.2 List of countries

Table 10: List of countries: B&B dataset

Argentina	Australia	Austria	Bangladesh
Belgium	Benin	Bolivia	Brazil
Cameroon	Canada	China	Colombia
Congo Rep. Of	Cote d'Ivoire	Denmark	Dominican Republic
Ecuador	Egypt	Finland	France
Ghana	Greece	Guatemala	Honduras
India	Indonesia	Ireland	Italy
Jamaica	Japan	Jordan	Korea
Malaysia	Mexico	Morocco	Nepal
Netherlands	New Zealand	Norway	Pakistan
Peru	Philippines	Portugal	Senegal
Sierra Leone	South Africa	Spain	Sweden
Thailand	Togo	Trinidad and Tobago	Tunisia
Turkey	United Kingdom	United States	Venezuela
Zambia	Zimbabwe		

Table 11: List of countries: Own dataset

Argentina	Australia	Austria	Bangladesh
Belgium	Benin	Bolivia	Botswana*
Brazil	Burundi*	Cameroon	Canada
Chile*	China	Colombia	Congo Rep. Of
Côte d'Ivoire	Denmark	Dominican Republic	Ecuador
Egypt	Finland	France	Germany*
Ghana	Greece	Guatemala	Haiti*
Honduras	India	Indonesia	Ireland
Italy	Jamaica	Japan	Jordan
Kenya*	Korea	Malaysia	Mauritania*
Mexico	Morocco	Mozambique*	Nepal
Netherlands	New Zealand	Nicaragua*	Niger*
Norway	Pakistan	Peru	Philippines
Portugal	Rwanda*	Saudi Arabia*	Senegal
Sierra Leone	Spain	South Africa	Sri Lanka*
Sweden	Switzerland*	Tanzania*	Thailand
Togo	Trinidad and Tobago	Tunisia	Turkey
Uganda*	United Kingdom	United States	Venezuela
Viet Nam*	Zambia	Zimbabwe	

Note: countries marked with a star are not in the B&B dataset. All other countries are common to both dataset.

A.3 Results from Clootens and Kirat (2017)

This section reproduces result obtained in Clootens & Kirat (2017). In this note, we use Brunnschweiler & Bulte (2008)'s dataset and methodology we and test its robustness to the omission of regional dummies (table 12). Then we take into account heterogeneity that may exist between OECD (northern) and non-OECD (southern) countries estimating separately the model on both subsample (table 13).

Table 12: Regressions with and without dummies

	With Dummies	Without Dummies
Economic Growth: *Growth*		
RD	-4.625 (3.130)	-9.996*** (3.604)
RA	0.345*** (0.127)	0.503*** (0.135)
$Inst$	1.666* (0.918)	1.596*** (0.498)
$gdp_{t=0}$	-2.073*** (0.804)	-1.806*** (0.511)
$afme$	-1.673*** (0.645)	
$eurca$	0.132 (1.142)	
aoc	-0.205 (1.156)	
nam	-0.433 (1.366)	
$cons$	14.400*** (3.807)	11.656*** (2.249)
Resource Dependence: *RD*		
$pres_{t=0}$	0.035 (0.022)	0.017 (0.021)
RA	0.016*** (0.005)	0.016*** (0.004)
$Inst$	-0.027 (0.017)	-0.027** (0.011)
$open$	0.259*** (0.040)	0.222*** (0.034)
$afme$	-0.011 (0.024)	
$eurca$	0.021 (0.039)	
aoc	0.035 (0.029)	
nam	0.030 (0.056)	
$cons$	-0.095* (0.055)	-0.063 (0.047)
Institutions: *Inst*		
$latitude$	2.920*** (0.585)	4.334*** (0.365)
RA	0.104*** (0.039)	0.088** (0.039)
$afme$	0.105 (0.201)	
$eurca$	0.870*** (0.302)	
aoc	0.591*** (0.214)	
nam	0.879** (0.440)	
$cons$	0.983*** (0.310)	1.056*** (0.254)
Observations	58	58

Notes: Robust standard errors in parentheses. *,** and *** refer respectively to the 10%, 5% and 1% significance levels.

Table 13: Regressions by subgroups

	Northern vs Southern		OECD vs non-OECD	
	Northern	Southern	OECD	non-OECD
Economic Growth: *Growth*				
RD	6.784 (8.549)	-10.724*** (4.073)	-3.207 (10.908)	-10.529*** (3.528)
RA	0.054 (0.087)	0.739*** (0.181)	0.025 (0.108)	0.939*** (0.185)
$Inst$	0.313 (0.660)	1.479** (0.723)	1.303* (0.716)	1.229 (0.955)
$gdp_{t=0}$	-1.585** (0.674)	-2.048*** (0.600)	-2.623*** (0.753)	-2.149*** (0.501)
$cons$	17.519*** (3.325)	12.207*** (2.548)	22.288*** (3.242)	12.225*** (2.567)
Resource Dependence: *RD*				
$pres_{t=0}$	-0.002 (0.011)	0.024 (0.029)	-0.005 (0.010)	0.025 (0.036)
RA	0.006** (0.003)	0.019*** (0.006)	0.007*** (0.002)	0.024*** (0.007)
$Inst$	0.002 (0.012)	-0.029 (0.023)	-0.006 (0.010)	-0.070 (0.056)
$open$	0.082*** (0.024)	0.265*** (0.046)	0.082*** (0.021)	0.265*** (0.049)
$cons$	-0.055 (0.041)	-0.096 (0.079)	-0.022 (0.036)	-0.037 (0.145)
Institutions: *Inst*				
$latitude$	3.814*** (0.952)	3.476*** (0.734)	3.257*** (0.830)	1.503** (0.660)
RA	0.036 (0.054)	0.100** (0.049)	0.056 (0.054)	0.058 (0.042)
$cons$	1.774*** (0.527)	1.115*** (0.343)	2.012*** (0.532)	1.608*** (0.292)
N	17	41	22	36

Notes: Standard errors in parentheses. *,** and *** refer respectively to the 10%, 5% and 1% significance levels.

A.4 First stages regressions

Table 14 presents first stage regressions of the instrumental procedure.

Table 14: First stages regressions

	B&B dataset	Own dataset
Mineral Dependence: *RD*		
$pres_{t=0}$	0.013 (0.027)	-0.007 (0.024)
RA	0.015*** (0.004)	0.011*** (0.003)
$\widehat{Inst}$	-0.035 (0.024)	-0.087*** (0.025)
$open$	0.223*** (0.061)	0.153*** (0.043)
$gdp_{t=0}$	0.010 (0.020)	0.038** (0.018)
$cons$	-0.101 (0.076)	-0.358** (0.151)
R^2	0.588	0.483
$Fstat$	F(5,52)=6.44	F(5,69)=5.97
Institutions: *Inst*		
$latitude$	2.202*** (0.414)	2.610*** (0.395)
RA	-0.009 (0.034)	-0.031 (0.027)
$gdp_{t=0}$	0.529*** (0.093)	0.318*** (0.081)
$pres_{t=0}$	-0.351* (0.179)	-0.435** (0.212)
$open$	-0.012 (0.232)	0.194 (0.264)
$cons$	-1.276* (0.665)	-2.967*** (0.737)
R^2	0.840	0.793
$Fstat$	F(5,52)=78.34	F(5,69)=107.33
N	58	75

Notes: Robust standard errors in parentheses. *,** and *** refer respectively to the 10%, 5% and 1% significance levels.

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