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Abstract

This paper analyzes the behavior of cross-country growth rates with respect to resource abundance and dependence. We reject the linear model that is commonly-used in growth regressions in favor of a multiple-regime alternative. Using a formal sample-splitting method, we find that countries exhibit different behaviors with respect to natural resources depending on their initial level of development. In high-income countries, natural resources play only a minor role in explaining the differences in national growth rates. On the contrary, in low-income countries abundance seems to be a blessing but dependence restricts growth.

Keywords: Non-renewable Resources; Growth; Resource Curse; Threshold Regressions.

JEL Codes: O11; O13; Q33.

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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. A number of transmission channels have been put forward in the literature to explain this curse. These channels can be split up into two categories: *economic* mechanisms and *political* explanations.

Among the economic transmission channels, 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; Matsen & Torvik, 2005). This refers to the over-evaluation of the local currency following the discovery and exploitation of a significant new resource deposit. This currency appreciation causes a loss of competitiveness in the secondary and tertiary sectors that are the engines of growth (increasing returns to scale and positive externalities are more likely to be found in the secondary and tertiary sectors than in the primary sector). Alongside the Dutch disease, we can note that mining is largely an enclave industry. As such, the extraction of mineral resources *per se* will produce relatively few positive spillovers for the rest of the economy (Davis & Tilton, 2005; Humphreys *et al.* , 2007). Abundant natural resources may also crowd out human-capital investment, increasing agents' opportunity costs of investing in human capital (Gylfason, 2001; Sachs & Warner, 1999). In addition, natural-resource discoveries shift investment from the secondary and tertiary sectors to the extractive industry, which is less likely to generate productivity gains (Sachs & Warner, 1995). The other main economic channels include resource-price volatility. The main source of revenues in resource-rich countries is often the extractive sector. However, resource prices can vary substantially, affecting the ability of governments to successfully manage their rent. The macroeconomic instability that results from resource-price volatility can also discourage investment (van der Ploeg & Poelhekke, 2009; Van der Ploeg & Poelhekke, 2010; Daniel, 1992).

The second transmission channel is political. Natural resources first generate rents, which may be misused. Resource rents allow governments to avoid or postpone unpopular but necessary structural reforms, and may also be devoted to unproductive welfare expenditures (Bomsel, 1992). Ross (1999) also notes that nationalized mining companies may soften the budget constraint of resource-exporting governments, *"producing fiscal laxity and a tendency to over-borrow"*. In addition, natural resources may encourage weak institutions: resource-rich countries are often characterized by centralized power and collusion between public authorities and the mining industry. Moreover, resource revenues may be used in order to mollify dissent, repress opposition and avoid accountability pressure (Karl, 1999). With weak institutions, natural resources incite rent-seeking behaviors by political interest groups. Those groups often ask for transfers that do not reflect economic contributions or social value. Corruption is also a major concern in resource-rich economies: politicians are often suspected of embezzling rents for their own personal gain or accepting bribes from third parties who wish to obtain or conserve access to the rent. Last, natural resources can generate conflicts for greed or grievance motives. Under the greed theory, rebels begin armed conflict in order to obtain access to or secure resource revenues. The grievance theory on the contrary suggests that rebels are motivated by the rising inequality that follow a resource boom (caused by rent-seeking, corruption and so on). In this latter case, social justice is the main source of conflict. There are obviously many causes of war, among which appear natural resources. These have been shown to often cause longer conflicts by providing the belligerents with revenues.

Alongside this transmission-channel literature, there has been great debate over the existing evidence for the existence of the resource curse, driven by the empirical observation that resource-rich countries have diverse experiences. As Nigeria's oil revenues rose sharply between 1966 and 2010, its real GDP per capita in constant PPP was multiplied by a factor of 2.2.[1] Equally, Botswana was one of the poorest countries in the world when it gained independence in 1966, but has enjoyed one of the highest growth rates over the past four decades thanks to its diamond deposits. Its GDP per capita in constant PPP rose by a factor of 14.8 over this period:[2] it is now one of the richest African countries and left the least-developed economies group in 1994.[3] Indonesia, Malaysia, and Thailand have also often been cited (together with Botswana) as developing resource-rich economies that have achieved a long-term investment ratio of over one quarter of GDP. While some suggest that these countries have escaped the resource curse, they still appear to have performed less well than their neighbors who have fewer raw materials: Hong Kong, Singapore and South Korea (van der Ploeg, 2011).[4] The World Bank estimates in Table 1 show that subsoil-asset and natural-capital shares are higher in low- and middle-income economies than in developed countries. Symmetrically, the intangible-capital share rises with the level of development.

[1] Nigeria's GDP per capita in constant PPP was 2240$ in 1966 and 5030$ in 2010 (source: Penn World Tables 9.0).

[2] Botswana's GDP per capita in constant PPP was 872$ in 1966 and 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), the Maldives (2011) and Mauritania and Samoa (2014). The group currently still includes 48 countries.

[4] Of course, these differences may be explained by other factors. Notably, James (2015) highlights the importance of industry in the economy and shows that there is little evidence that resource abundance hampers non-resource growth.

Table 1: Total wealth and subcomponents 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: These are per capita figures. Source: Own calculations based on World Bank (2011).

Growth regressions are often used to investigate the resource curse. The growth regressions in the seminal paper by Sachs & Warner (1995) show that the natural-resource share of exports is negatively correlated with economic development. They then extend their work to show that there is little evidence that the curse is explained by omitted geographical variables (Sachs & Warner, 2001). Atkinson & Hamilton (2003) use growth regressions to suggest that the resource curse reflects the inability of governments to manage large resource revenues in a sustainable way. Papyrakis & Gerlagh (2004) also use growth regressions to analyze resource-curse transmission channels. Alongside these positive analyses, some normative work also relies on growth regressions. Among others, Sala-i Martin & Subramanian (2008) suggest that resource-rich economies (and, more precisely, Nigeria) should directly distribute their oil revenues to the population.

The use of growth regressions in this literature is often accompanied by two sizeable problems, as highlighted in Brunnschweiler & Bulte (2008): *i)* natural-resource exports over GDP captures resource dependence rather than resource abundance, and their use as a proxy for abundance may lead to the misinterpretation of the regression results; and *ii)* introducing resource dependence and institutional variables in growth regressions may lead to endogeneity bias, as resource-dependence is related to economic choices that may simultaneously affect growth. Natural resources can also reduce institutional quality, which in turn affects resource dependence through the economic policies that depend on institutions. The authors address this endogeneity problem via Three-Stage Least Squares (3SLS) regressions using historical openness and having a Presidential regime in the 1970s as instruments for resource dependence, while institutional quality is instrumented by latitude.[5] 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.

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 do exhibit considerable heterogeneity in terms of climate, geology, culture, politics and economics. Using the same dataset, Clootens & Kirat (2017) show that the impact of resource dependence on growth becomes strongly negative and significant when the regional dummies are omitted. Moreover, the way in which Brunnschweiler & Bulte (2008) take regional heterogeneity into account constrains the model parameters (apart from the constant) to be identical across regions. Durlauf & Johnson (1995) show that the linear model that is commonly used to analyze growth behavior may be misspecified, and argue for a multiple-regime alternative.

Clootens & Kirat (2017) relax this linearity assumption and allow all estimated parameters to vary by region. They split the sample into two distinct regions: the Northern and Southern countries.[6] As this split is subjective, they also look at OECD versus non-OECD countries. They find that Southern (non-OECD) and Northern (OECD) economies have different relations to resource dependence: resource dependence reduces

[5] Other popular instruments appear in their robustness checks: the results remain unchanged.

[6] This split is effected using the areas in Brunnschweiler & Bulte (2008). The Northern countries include the North-American, European and Central-Asian countries. They do not consider African and Middle-Eastern countries against the rest of the world separately, as there are too few observations in the sub-sample of African and Middle Eastern countries.

growth in low-income economies.

The sample split in Clootens & Kirat (2017) is subjective, and could be improved by the use of formal sample-splitting methods. Konte (2013) argues that the impact of natural resources on growth may depend on the growth regime to which the country belongs. Using regression-mixture methods, she shows that natural resources increase growth in some countries but reduce it in others. We here use the sample-splitting approach in Hansen (2000) to test for a threshold effect, and estimate the threshold endogenously. We believe that this approach has notable advantages, as it corrects for potential endogeneity bias provided that our splitting variable is exogenous.[7] Using two different datasets, we find that there exists a value of initial GDP that allows the sample to be split in two. As initial GDP might not be endogenous, we estimate the threshold and run regressions on our sub-samples. We find that resource dependence reduces growth in low-income economies, while resource abundance there is on the contrary a blessing. Growth in high-income countries is not significantly affected by either abundance or dependence.

The remainder of the paper is organized as follows. Section 2 describes our datasets and Section 3 sets out the estimation strategy. Section 4 then presents the results and their interpretation. Section 5 provides the standard tests and robustness check, and last Section 6 concludes.

[7]Caner & Hansen (2004) show that this method allows the use of instrumental variables instead of ordinary least squares if the model suffers from endogeneity.

2 Data

Our econometric analysis below will be carried out on two separate datasets.[8] The first is that in Brunnschweiler & Bulte (2008) (called B&B hereafter), which covers the 1970-2000 period. The second (our own) covers the period 1980-2014 and includes new countries.[9]

In the B&B dataset, $Growth$ refers to the average log-growth of real (PPP in current \$) GDP per capita between 1970 and 2000, and $gdp_{t=0}$ represents real (PPP in current \$) GDP per capita in 1970. Resource dependence (RD) is measured as the GDP share of mineral exports (the sum of mineral fuels, ores and metal exports[10]) averaged over 1970-1989, while resource abundance (RA) is the log of subsoil assets in \$ per capita in 1994.[11] This 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 for the regime being Presidential (1) or Parliamentary (0). The first entry in 1970s is retained. Last, trade openness (*open*) is the (nominal) GDP share of imports plus exports averaged over the 1950s and 1960s.

In our dataset, $Growth$ is the average log-growth in real (PPP in constant \$) GDP per capita between 1980 and 2014. The Penn World Tables 9.0 provide five GDP estimates: we here use real GDP calculated using national-accounts growth rates, as recommended for growth regressions by Feenstra *et al.* (2015).[12] We also follow the recommendation

[8]The data sources are provided in Appendix A.1.

[9]We systematically reproduce our analysis on the data in Brunnschweiler & Bulte (2008) to check that the results are not driven by our choice of data. Moreover, we carry out a robustness check using updated data from PWT 9.0 for the 1970-2000 period.

[10]Fuels are the commodities in Standard International Trade Classification (SITC) 3, while ores and metal are those in SITC 27, 28 and 68.

[11]Taking the log we replace 0 by missing values. It can be argued that this produces a bias in the results.

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

in Feenstra *et al.* (2015) when choosing our initial GDP variable, and take real GDP in current PPP in 1980. This choice limits the bias that may be introduced by the "constant PPP correction" and is the best measure of initial GDP. Concerning RA, we use the log of subsoil assets per capita in $ in 1994 plus one, and can so include countries with no mineral assets in our regressions. Adding one to the subsoil-asset figure does not introduce much distortion as the non-zero values for subsoil assets are quite high. Our RD variable is the average GDP share of mineral exports (defined as in the B&B dataset) over the 1980-2014 period. Our $Inst$ variable also captures the effectiveness of contract enforcement, police and the courts, and the likelihood of crime and violence, and is an average over the period to better represent "average" institutional quality over the period considered. For $pres_{t=0}$ we retain the first entry in 1980s. Last, our trade-openness variable is the average real (current PPP) GDP share of imports and exports over the 1970s. We do not consider previous periods in order to maximize the number of observations in the database.

Finally, *latitude* is common to both datasets. This is the country capital's latitude in absolute value, divided by 90 to produce a figure 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 appears in Appendix A.2. The two datasets contain respectively 58 and 75 countries.

Table 2 presents the descriptive statistics for both datasets. The left-hand side refers to the B&B dataset and the right-hand side our own. The statistics are similar except for growth and institutions. For *growth*, these differences are mainly due to the way in which the variable is calculated: our growth variable takes into account PPP changes over time following progress in the recent Penn World Tables.[13] The difference in $Inst$ reflects our inclusion of new countries.

3 Estimation strategy

3.1 The threshold model

The main equation in the linear model of Brunnschweiler & Bulte (2008) is very similar 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 of initial GDP per capita (in the starting period). The choice of the transition variable among the explanatory variables for threshold models is key. In many papers, this choice comes from economic theory. We here appeal to the literature on convergence clubs to identify initial real GDP per capita as the threshold variable. The

[13] Multiple GDP variables appear in PWT 9.0. There is a conversion table to previous versions.
[14] We omit the regional dummies.

idea is to show that there are different growth trajectories, depending on initial GDP. We believe that these differences can be measured by the asymmetry of long-run GDP growth relative to initial GDP.[15] Hansen (2000) uses initial GDP as the threshold variable in growth regression to distinguish multiple equilibria. This idea was inspired by Durlauf & Johnson (1995), who suggest that cross-section growth may be determined by initial conditions. Clootens & Kirat (2017) uncover some evidence that countries do react differently to an increase in resource dependence by their initial level of GDP. We thus consider 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 as unknown. It is convenient to rewrite (3) as follows:

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

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 this 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 carry out statistical inference regarding λ. In this case q is a nuisance parameter that is not identified under the null hypothesis. Hansen (1996) avoids this problem via a simulation technique producing a p-

[15] Other work identifies the threshold variable via a test procedure applying linearity tests to each of the explanatory variables. The threshold variable is then selected as that with the lowest risk of error when linearity is rejected. This statistical approach has no theoretical economic foundation, and thus presents the disadvantage of potentially selecting a threshold variable that differs from the theoretically-based variable of interest. For this reason many authors opt for the approach we take here.

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 calculation of the threshold estimate $\widehat{q}$ uses the concentrated sum of squared errors function from (4):

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

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 calculated using $\widehat{\Psi^2}(\widehat{q})$ and $\widehat{\lambda}(\widehat{q})$. Hansen (2000) and Caner & Hansen (2004) have also developed asymptotic-distribution theory for the threshold estimate $\widehat{q}$, and propose asymptotic confidence intervals by inverting the likelihood-ratio statistic. This approach also allows for possible heteroskedasticity in (4).

3.2 Dealing with endogeneity

Endogeneity is a central issue in threshold models. Threshold regression requires the exogeneity of regressors in equation (1), otherwise the estimates will be biased. Brunnschweiler & Bulte (2008) identify a number of sources of endogeneity.[16] For instance, taking institutional quality and resource dependence as exogenous variables may lead to biased outcomes. Institutional quality might be linked to variables such as culture or other

[16] Haber & Menaldo (2011) concur with this point and argue that cross-country growth regressions for the resource curse may suffer from omitted variables and reverse-causality bias. Instrumentation should correct for these biases. Moreover, our sample-splitting may reduce the omitted-variable bias as we group countries according to their initial level of income. We nevertheless acknowledge that our results should not necessarily be read as being set in stone.

omitted variables that also determine growth. Moreover, RD is not a proper explanatory variable in growth regressions as its denominator is GDP, which is likely correlated with various determinants of economic growth.

Another concern is the exogeneity of the resource-abundance variable: the exploration and evaluation of resource stocks is a technologically-intensive process that is not independent of countries' technological levels. Nevertheless, thanks to their economic potential, mineral deposits have been explored and estimated by large multinational firms regardless of the local conditions. While the resource-abundance variable is not free from criticism,[17] we believe that it constitutes a significant improvement with respect to the standard measure popularized by Sachs & Warner (1995).

The literature has typically used three alternative instruments to control for the endogeneity bias introduced by institutions: latitude, the fraction of population speaking a Western-European language (Hall & Jones, 1999) and the logarithm of settler mortality (Acemoglu *et al.* , 2001). Latitude and the fraction of population speaking a Western language are measures of the extent to which the economy has been influenced by Western Europe, as this was the first area to introduce institutions supporting production. Nevertheless, these variables are not affected by current economic performance.[18]

According to Acemoglu *et al.* (2001), settler mortality is also a good instrument for institutions, as there were various types of colonization ranked from "extractive states" to "neo-Europes" (Crosby, 2004). The feasibility of settlements affected the colonization strategies such that "neo-Europes" appeared where settler mortality was low. As past in-

[17]Notably, Bohn & Deacon (2000) remark that economic policies may affect the present value of rents. Van der Ploeg & Poelhekke (2010) are also suspicious of 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 which were proposed in the critical paper by Van der Ploeg & Poelhekke, 2010) we do not enter into this debate here.

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

stitutions are a major determinant of current institutional quality, settler mortality seems to be a good instrument for institutions. We here use latitude to instrument institutions, as it is likely that mineral abundance promoted the establishment of extractive states.

We distinguish two institutional perspectives, following Brunnschweiler & Bulte (2008). First, institutions can be seen as persistent constitutional variables (Presidential vs. Parliamentary regimes, electoral rules etc.) and refer to the "deep and durable" characteristics of a society (Glaeser *et al.* , 2004). On the other hand, institutions can also refer to the policy outcomes in property-rights enforcement, the fight against corruption and so on (Rodrik *et al.* , 2004). Our variable $Inst$ is of the second type, and may be endogenous when used in the second-step estimation. We therefore need to instrument it in a first step.

Deep and durable institutions can be used to instrument resource dependence. Brunnschweiler & Bulte (2008) use a dummy variable (for the country having a Presidential regime in the 1970s) as a proxy for institutions. Presidential regimes are often associated with public expenditures that are biased in favor of private interests (including the primary sector), as the decision-maker does not have to rely on a stable majority. They show that this variable is exogenous and that past trade openness is a good instrument for RD.[19]

To avoid endogeneity issues in threshold estimation, we here use the predicted values of the RD and $Inst$ variables from instrumental equations (or first-step instrumental-variable estimations) instead of their observed values. The instrumentation procedure that we use here follows that in Brunnschweiler & Bulte (2008).

[19]The use of the predicted trade shares developed by Frankel & Romer (1999) as an instrument for potentially endogenous trade openness does not affect their results.

4 Results

We first carry out 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

$$\widehat{RD}_i = \widehat{\psi}_0 + \widehat{\psi}_1 RA + \widehat{\psi}_2 gdp_{t=0,i} + \widehat{\psi}_3 latitude_i + \widehat{\psi}_4 open_i + \widehat{\psi}_5 pres_{t=0,i} \tag{8}$$

and

$$\widehat{Inst}_i = \widehat{\phi}_0 + \widehat{\phi}_1 RA + \widehat{\phi}_2 gdp_{t=0,i} + \widehat{\phi}_3 latitude_i + \widehat{\phi}_4 open_i + \widehat{\phi}_5 pres_{t=0,i} \tag{9}$$

In equation (7), $\widehat{RD}$ and $\widehat{Inst}$ are the predicted values from the instrumental regressions (8) and (9). Figure 1 depicts the outcome of the threshold test in both datasets. If the resulting figure is above the 95% critical value then linearity is rejected.

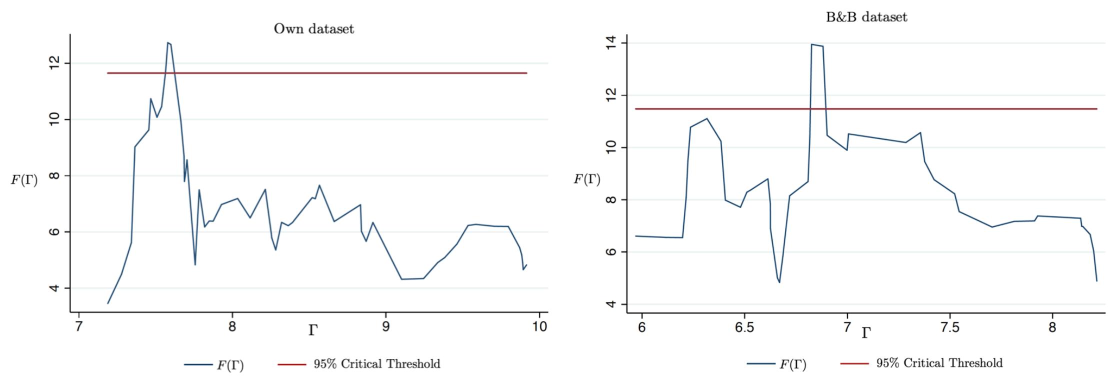

Figure 1: Threshold tests: the IV case

Notes: The F-Test for threshold rejects linearity if the F-Statistic is above the 95% critical value. Linearity is thus rejected in both datasets.

The test rejects the null hypothesis of linearity in both datasets. The reported p-values in the B&B and our own dataset are respectively 0.022 and 0.049.[20] There is then a threshold value of initial GDP that splits our sample into two subsamples, consistent with Clootens & Kirat (2017). Sample-splitting estimation should then be carried out for both datasets.

Table 3: IV regressions by subgroups

	Own dataset			B&B dataset		
Economic growth:	All	Low	High	All	Low	High
RD	-0.064	-0.287**	0.006	-0.100***	-0.106*	-0.007
	(0.039)	(0.124)	(0.035)	(0.036)	(0.064)	(0.025)
RA	0.002***	0.010*	0.000	0.005***	0.009***	0.000
	(0.001)	(0.006)	(0.001)	(0.001)	(0.002)	(0.001)
$Inst$	0.009**	-0.012	0.010***	0.016***	0.027**	0.011**
	(0.004)	(0.042)	(0.004)	(0.005)	(0.012)	(0.005)
$gdp_{t=0}$	-0.011***	-0.048**	-0.011***	-0.019***	-0.027***	-0.014*
	(0.003)	(0.024)	(0.003)	(0.005)	(0.009)	(0.008)
$cons$	0.100***	0.337**	0.105***	0.159***	0.197***	0.154***
	(0.023)	(0.136)	(0.028)	(0.035)	(0.058)	(0.058)
$Threshold$	———	7.468	7.468	———	6.826	6.826
N	75	16	59	58	29	29
$AndersonLM - Stat$	16.355 ($\chi^2(2)$)	———	———	21.177 ($\chi^2(2)$)	———	———
$Sargan - HansenJ - Stat$	0.160 ($\chi^2(1)$)	———	———	0.023 ($\chi^2(2)$)	———	———

Notes: Standard errors in parentheses. *,** and *** refer respectively to the 10%, 5% and 1% significance levels. The first-step results for the main regressions appear in Appendix A.4. The threshold is estimated at the 95% confidence interval.

Table 3 confirms the insights in Clootens & Kirat (2017) regarding the need for sample splitting: poor and rich countries (defined using the method in Hansen (2000)) do not react in the same way with respect to natural resources. In low-income economies, resource dependence is a curse that reduces growth possibilities, while resource abundance remains a blessing. In the B&B dataset, a one percentage-point rise in the GDP share of mineral exports leads to a fall of 0.106 percentage points (0.287 in our dataset) in growth. However, one percent higher subsoil assets are associated with higher growth of about 0.009 percentage points (0.010 in our dataset). The negative sign on initial GDP per capita reflects catch-up. One percent higher initial GDP reduces the average growth rate by 0.027 percentage points (0.048 in our dataset). In the B&B dataset,

[20] These are bootstrapped p-values with 5000 replications. In our own dataset, we carry out the test a number of times. The p-value varies a little between replications, and we never find a p-value of over 0.06.

one percentage-point higher institutional quality is associated with growth that is 0.027 percentage points higher (with no significant effect in our dataset).

In high-income economies, growth is neither determined by dependence nor abundance. Institutional quality does seem to play an important role, while we also find a catch-up effect in both datasets.

The results for mineral dependence contradict one of the principal results in Brunnschweiler & Bulte (2008):[21] we find that with sample splitting, resource dependence matters for the growth of developing economies. Initial GDP per capita is typically introduced in growth regressions to reflect catch-up. Here, this variable also acts as the sample-splitting variable to take into account the heterogeneity of countries with respect to their stage of development. Implicitly, by choosing this variable to split the sample, we suppose that countries on each side of the threshold share common properties in a way that is determined by their development. Notably, we believe that a country with high income per capita in 1970 (or 1980, depending on the dataset) is probably a country with a market-friendly environment: a more-educated population, developed financial markets, sufficient trade openness, institutional quality, a high level of investment, and so on.[22] These shared characteristics help high-income economies compensate for the negative impact that natural resources may have on economic performance. For example, the probability of civil conflict falls with education. Moreover, the potential cost that will

[21]We believe that our results help to understand those in Brunnschweiler & Bulte (2008). They introduce regional dummies in their regression, but the only significant coefficient is for Africa and the Middle East. These dummies are introduced to control for geographical (cultural, climatic, natural, geological etc.) unobserved characteristics. Our results suggest they capture something quite different. The regional dummies proposed cover a very large area with very different countries: South Africa, Jordan, Tunisia and Togo (for example) seem to be sufficiently distant to not have common geographical characteristics. As Africa is the poorest continent, we believe that the dummies capture unobserved differences that are strongly linked to initial development.

[22]While some of those variables may be biased for endogeneity reasons, our approach has the advantage of classifying countries into two groups with common properties without any subjective choice on our part, except that of the threshold variable.

be incurred by the failure of rebellion is higher in high-income economies. Developed markets may also reduce rebellion for grievance reasons, and help to absorb shocks to resource prices. Greater (unobserved) institutional quality implies less corruption and misappropriation of public revenue. The Dutch disease or other crowding-out mechanisms associated with natural resources are easier to counter with appropriate economic policy when markets are developed.

As we may think that resource abundance generates dependence, we would like to calculate the net effect of natural-resource abundance on economic growth. We can do so in our first-stage IV estimates (see Appendix A.4). We conclude that the net effect of resource abundance is such that a one percent rise in subsoil assets generates an average increase in growth of about 0.00656 percentage points in both datasets. We should nevertheless be cautious regarding this figure, and believe that there is some potential for a resource-dependence curse. However, if resource abundance does improve growth there is no universal resource curse: resource abundance does not necessarily reduce growth, even if greater resource dependence does hamper growth in low-income economies.

5 Conclusion

This paper has added the work of Brunnschweiler & Bulte (2008) by improving the treatment of heterogeneity between countries. We notably use the sample-splitting method in Hansen (2000) on the same dataset that Brunnschweiler & Bulte (2008) use. One of their main results is affected by the sample split: resource dependence only negatively affects development in low-income countries (but has no effect in high-income countries). We acknowledge that this result is not independent of the choice of the threshold variable. While our method allows us to test for and estimate the value of the threshold without any subjective considerations, we still have to choose the threshold variable. Initial GDP is highly correlated with human capital, current trade-openness, market development etc. We believe that high-income economies share a number of common properties that allow them to limit the negative effects of natural resources on growth. We thus argue that developing education, financial markets and institutions may restrict the negative influence of resource dependence on growth. Moreover, since resource dependence results from economic choices, it can be avoided by an appropriate diversification policy.

To summarize, we highlight that it is difficult to promulgate universal laws, such as natural-resource abundance is a blessing or a curse. We argue that while, on average, resource abundance favors growth in low-income economies, there does also exist some evidence for a resource-dependence curse.

A.1 Data sources

The following table describes the data source for each variable.

Table 4: 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 for providing their entire dataset on Christa Brunnschweiler's personal website.

A.2 List of countries

Table 5: 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 6: 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
Vietnam*	Zambia	Zimbabwe	

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

A.3 Ranking of countries according to their initial GDP

Table 7: Country initial GDP (B&B dataset)

Country	$GDP_{t=0}$	Country	$GDP_{t=0}$
China	5.49	Guatemala	6.88
Nepal	5.50	Jamaica	6.90
Indonesia	5.52	Turkey	7.00
India	5.77	Brazil	7.01
Bangladesh	5.80	Peru	7.28
Benin	5.88	Trinidad and Tobago	7.36
Congo Rep. Of	5.96	Venezuela	7.38
Pakistan	5.97	Mexico	7.42
Sierra Leone	6.17	Portugal	7.52
Cameroon	6.20	South Africa	7.54
Togo	6.21	Ireland	7.71
Senegal	6.22	Greece	7.81
Ghana	6.24	Spain	7.91
Honduras	6.32	Argentina	7.93
Jordan	6.38	Italy	8.13
Thailand	6.41	Austria	8.14
Morocco	6.48	Finland	8.15
Egypt	6.51	Japan	8.18
Dominican Republic	6.53	United Kingdom	8.20
Philippines	6.61	Belgium	8.22
Ecuador	6.62	France	8.23
Zimbabwe	6.63	Norway	8.25
Bolivia	6.66	New Zealand	8.30
Korea	6.67	Netherlands	8.31
Tunisia	6.69	Canada	8.32
Malaysia	6.72	Australia	8.41
Cote d'Ivoire	6.81	Sweden	8.43
Colombia	6.82	Denmark	8.47
Zambia	6.83	United States	8.52

Table 8: Country initial GDP (Own dataset)

Country	$GDP_{t=0}$	Country	$GDP_{t=0}$
Mozambique	6.27	Jordan	8.32
Nepal	6.60	Tunisia	8.36
Uganda	6.60	Argentina	8.39
Burundi	6.64	Nicaragua	8.52
Viet Nam	6.94	Brazil	8.54
Rwanda	7.00	Republic of Korea	8.57
Sierra Leone	7.04	Ecuador	8.66
India	7.06	Chile	8.83
Bangladesh	7.10	Colombia	8.84
Egypt	7.14	Malaysia	8.87
Niger	7.19	Turkey	8.91
Zambia	7.27	South Africa	9.10
Senegal	7.34	Portugal	9.24
China	7.36	Venezuela	9.34
Togo	7.45	Mexico	9.38
Haiti	7.47	Ireland	9.46
Tanzania	7.51	Greece	9.53
Benin	7.54	Spain	9.59
Cameroon	7.56	New Zealand	9.70
Kenya	7.58	Austria	9.80
Pakistan	7.60	Finland	9.87
Sri Lanka	7.66	Japan	9.88
Botswana	7.68	United Kingdom	9.89
Ghana	7.69	Germany	9.89
Bolivia	7.69	Italy	9.92
Mauritania	7.70	Sweden	9.92
Indonesia	7.76	Trinidad and Tobago	9.96
Côte d'Ivoire	7.78	Denmark	9.97
Zimbabwe	7.82	Belgium	9.99
Congo	7.85	France	10.01
Morocco	7.87	Australia	10.02
Honduras	7.93	Netherlands	10.09
Philippines	8.03	Canada	10.14
Thailand	8.11	Norway	10.20
Guatemala	8.21	United States	10.28
Dominican Republic	8.25	Switzerland	10.37
Peru	8.26	Saudi Arabia	10.81
Jamaica	8.28		

A.4 First-stage regressions

Tables 9 and 10 present the first-stage regressions for the instrumentation.

Table 9: First-stage regressions: B&B dataset

	All	Low	High
Mineral Dependence: RD			
RA	0.016*** (0.005)	0.022** (0.009)	0.011* (0.006)
$gdp_{t=0}$	-0.009 (0.014)	-0.048 (0.036)	0.020 (0.030)
$pres_{t=0}$	0.025 (0.020)	0.044 (0.032)	-0.001 (0.029)
$latitude$	-0.077 (0.065)	0.054 (0.118)	-0.225** (0.089)
$open$	0.223*** (0.036)	0.286*** (0.074)	0.213*** (0.046)
$cons$	-0.056 (0.086)	0.093 (0.217)	-0.170 (0.212)
R^2	0.588	0.565	0.699
$F\ stat$	14.83	5.97	10.68
Institutions: $Inst$			
RA	-0.009 (0.036)	-0.004 (0.062)	-0.010 (0.038)
$gdp_{t=0}$	0.530*** (0.102)	0.611** (0.260)	1.075*** (0.194)
$pres_{t=0}$	-0.351** (0.147)	-0.380* (0.220)	-0.215 (0.188)
$latitude$	2.202*** (0.463)	1.399 (0.819)	1.822*** (0.575)
$open$	-0.012 (0.260)	-0.608 (0.511)	0.323 (0.299)
$cons$	-3.776*** (0.615)	-3.829** (1.500)	-8.144*** (1.366)
R^2	0.840	0.373	0.897
$F\ stat$	54.72	2.74	40.11
N	58	29	29

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

Table 10: First-stage regressions: Own dataset

	All	Low	High
Mineral Dependence: RD			
RA	0.012*** (0.003)	0.008 (0.006)	0.015*** (0.001)
$gdp_{t=0}$	0.015 (0.010)	-0.009 (0.042)	0.028** (0.016)
$pres_{t=0}$	0.030 (0.019)	0.025 (0.054)	0.028 (0.024)
$latitude$	-0.210*** (0.052)	-0.083 (0.133)	-0.281*** (0.70)
$open$	0.107*** (0.030)	0.197** (0.065)	0.134*** (0.039)
$cons$	-0.130 (0.078)	0.047 (0.285)	-0.249** (0.125)
R^2	0.475	0.615	0.512
$F\ stat$	12.47	3.20	11.12
Institutions: $Inst$			
RA	0.007 (0.025)	0.095 (0.053)	-0.043 (0.031)
$gdp_{t=0}$	0.309*** (0.081)	-0.370 (0.323)	0.404*** (0.115)
$pres_{t=0}$	-0.507*** (0.153)	-0.497 (0.418)	-0.359** (0.174)
$latitude$	2.472*** (0.420)	0.237 (1.026)	2.591*** (0.519)
$open$	0.039 (0.240)	-0.132 (0.505)	0.224 (0.287)
$cons$	-2.858*** (0.637)	2.118 (2.202)	-3.740*** (0.926)
R^2	0.804	0.466	0.797
$F\ stat$	56.64	1.75	41.68
N	75	16	59

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

A.5 The OLS regression

If there are no endogeneity problems in the data, a simple OLS regression is more efficient than a 2SLS regression. We believe that there are good reasons to suspect endogeneity

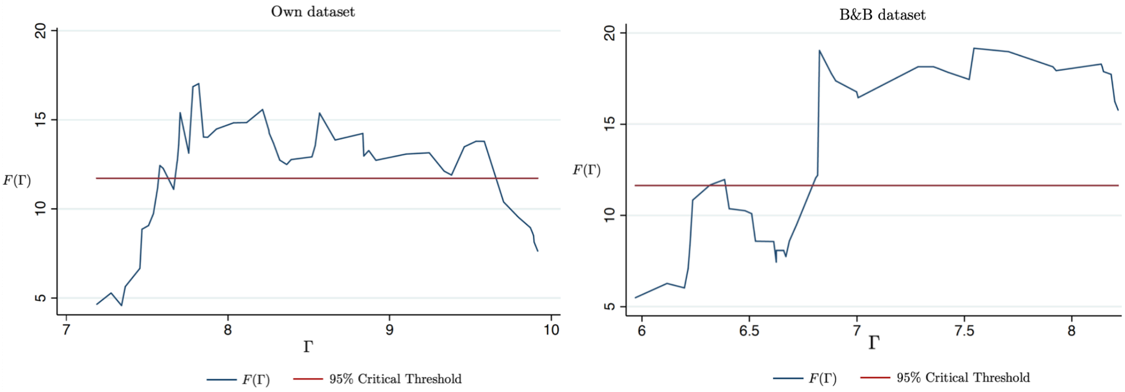

Figure 2: Threshold tests: the ols case

Notes: The F-Test for threshold rejects linearity if the F-Statistic is above the 95% critical value. Linearity is thus rejected in both datasets.

and use 2SLS. Nevertheless, robustness checks using OLS are of interest. The threshold-test results with uninstrumented data appear in Figure 2. The threshold test concludes for the rejection of the null hypothesis of linearity in both datasets. Table 11 presents the results of the threshold OLS estimations.

Table 11: OLS regressions by subgroups: Own dataset

	(1)	(2)	(3)	(4)	(5)	(6)
Economic growth:	All	Low	High	Low^{LB}	High^{LB}	Low^{UB}
RD	-0.028	-0.106**	-0.002	-0.051**	-0.105***	0.029
	(0.019)	(0.047)	(0.017)	(0.024)	(0.033)	(0.019)
RA	0.002***	0.003**	0.001	0.004***	0.009***	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
$Inst$	0.012***	0.024***	0.010***	0.018***	0.024***	0.013***
	(0.002)	(0.006)	(0.002)	(0.003)	(0.005)	(0.003)
$gdp_{t=0}$	-0.012***	-0.016**	-0.012***	-0.019***	-0.026***	-0.015**
	(0.002)	(0.007)	(0.003)	(0.004)	(0.007)	(0.006)
$cons$	0.112***	0.142**	0.119***	0.162***	0.189***	0.170***
	(0.017)	(0.052)	(0.024)	(0.025)	(0.045)	(0.044)
$Threshold$	———	7.784	7.784	———	6.826	6.826
N	75	27	48	58	29	29
R^2	0.381	0.578	0.405	0.442	0.684	0.481

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

The results confirm those above: RD has a negative impact on growth while RA is a blessing for low-income economies. There is still a catch-up effect in this group, while $Inst$ becomes significant, which is as expected as OLS implies an efficiency gain with respect to IV in the absence of endogeneity. Neither natural-resource abundance nor dependence affect growth in developed economies.

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