UNIVERSITY OF CANTERBURY

Department of Economics and Finance

PhD Confirmation Report

An Investigation of the Resource Curse in Indonesia

Candidate

Rian Hilmawan

Supervisors

Assoc. Prof. Jeremy Clark

Dr. Andrea Menclova

2017

Table of Contents

List of Tables

List of Figures

Figures Page

1 Introduction

1.1 Background

In the 1960's, there was a strong belief that a country's natural resources determined the quality of its economic performance. A prominent proponent of this view was the development economist Walter Rostow, who argued that a country's natural resource endowment played a crucial role in its "take-off" process, or its period of transition from being a traditional society based on a primary sector to a more industrialized society with high consumption (Rostow, 1961).

Similarly, in the late 1980's, neo-classical economists such as Douglas North stressed the significance of natural resource stocks as a driving component of a society's long-term output (North, 1982).[1] North argued that, historically, natural resources played an essential role in the United States' transition to being a dominant economy by the early twentieth century. Natural resources have also been credited as the main factor behind the history of the great economic development of countries beyond the United States, such as Canada, Australia, and Finland, enabling them to outperform other countries' development in the world (Lederman and Maloney, 2008). Thus, until the late 1980's at least, natural resources were generally viewed by economists as an advantage that can sustain and promote economic growth without exception.

By the early 1990's, however, this positive view of the role of resources in development seemed to face an empirical challenge. Many nations with an abundance of natural resources, primarily located in Africa, the Middle East, and Latin America, have tended to have weak income levels and unstable growth rates and have obtained worse performance on broader development indicators when compared to resource-scarce countries elsewhere. Auty (1994) was the first to label this counter-intuitive result a "resource curse". This term can be defined as the negative impact of natural resource wealth on economic growth or economic performance.[2] In a more recent treatment, Humphreys, Sachs, and Stiglitz (2007) emphasize the resource curse phenomenon using broader

---

[1] North modelled the influence of natural resources using a society's aggregate production function $Y = F(N, T, R, P, H)$, where Y is output, N stands for the society's stock of knowledge, T denotes its technological stock, R is its endowment of natural resources, and P and H refer respectively to its stock of labor and human capital (See North (1982), pages 15-16).

[2] Economic performance is commonly measured using real Gross Domestic Product (GDP) per capita, whether in levels or changes.

outcome measures than income or output, such as indicators of social development and good governance.

The first empirical paper to test Auty's "resource curse" was by Sachs and Warner (1995). Sachs and Warner conduct a large pooled cross-country study over twenty years (1970-1989) to test the relationship between what they called natural resource "abundance" and growth in income. They find an inverse association on average. Auty's proposed resource curse, and Sachs and Warner's confirmation of it, has sparked continuous attention from academics and practitioners. As of 2017, there have been hundreds of studies testing the relationship between natural resources and economic growth. These studies have been compiled and discussed in several surveys, which not only summarize some important findings in the previous empirical studies, but also criticize their methods and make suggestions for further analysis (Badeeb, Lean, & Clark, 2017; Aragon, Chuhan-Pole and Land (2015); Cust & Poelhekke, 2015b; Frankel, 2010; Alexander James, 2015; Papyrakis, 2016; Ploeg, 2011; van der Ploeg & Poelhekke, 2016)

Some studies have confirmed a negative and significant effect of natural resources on economic growth. In contrast, others have found a positive impact, while yet others have found no significant relationship. Each has sought to ask whether resources are on average a curse or a blessing.

Several prominent papers in this literature can illustrate these disparate findings. Gylfason (2001) uses data from 85 countries between 1965-1998 to set a regression line through a scatterplot, and finds that natural resource "abundance" (measured as the share of each nations's natural capital over national wealth in 1994) is negatively associated with its per capita growth in GDP. In doing so, Gylfason also finds a similar negative result when he tries another resource intensity measure, the share of the primary sector in each nation's total employment. Supporting this finding, Papyrakis and Gerlagh (2004) find that natural resources strongly reduce growth indirectly through their effects on intermediate variables. These indirect effects work through increasing corruption, lowering incentives for investment, reducing openness, worsening a nation's terms of trade and weakening demand side incentives for schooling.

In contrast, some later 'resource curse' researchers have found a positive association between countries' resource production intensity and their economic outcomes, and have expressed skepticism about the original results of Sachs and Warner. Brunnschweiler

(2008), for example, estimates a direct positive relationship between natural resource production (specifically mineral and fuel production per capita) on economic growth. Similarly, Brunnschweiler and Bulte (2008) find no significant link between resource dependence (defined as the average of mineral exports as a share of GDP over the period 1970-1989) and growth, and instead a positive direct association between resource abundance (measured as subsoil wealth) and growth in GDP. A more recent study by Alexeev & Conrad (2016) also finds positive effects on per capita GDP of both resource dependence (measured as value of oil production over GDP) and of resource abundance (estimated oil reserves). Alexeev and Conrad (2009, 2011) similarly find positive effects of oil resources on per capita GDP for the transition economies of formerly socialist countries.

The journey of empirical resource curse analysis begun by Sachs and Warner in 1995 has tended to use macro-country level datasets, especially geared to include low or middle-income countries. Thus, the main empirical approaches have predominantly used cross-country comparisons. For example, Sachs and Warner (1995) used pooled cross-section international data on each country's average annual growth rate between 1971-1990. The same approach was followed by Gylfason (2001), Mehlum, Moene, and Torvik (2006), Papyrakis and Gerlagh (2004). Some researches have used country fixed effects rather than pooled cross section in order to control for stable, unobserved country-level variables that affect growth (Torvik (2009); Lederman & Maloney (2003)). Some early studies have found an inverse association also holds in country fixed effects analysis (Collier and Goderis 2009).

Particularly in the late 1990's and early 2000's, when evidence for the resource curse seemed strongest, scholars developed several major causal explanations by which it might operate. These causal channels provided plausible mechanisms through which natural resources could ultimately hamper economic achievement in resource-rich economies.[3] The first channel identified was the "Dutch Disease".[4] Sachs and Warner (1995) write that the Dutch Disease can delay growth, because it makes countries rely predominantly on resource exports. It then crowds out the performance of non-resource sector exports, such as the manufacturing sector. Gylfason (2001) adds that natural resource exploitation crowds out human capital accumulation by reducing the incentive for young people to remain in school

[3] Other potential channels for the resource curse that have been identified by others will not be pursued here, such as volatility of commodity prices relative o non-commodity prices.
[4] Initially, this label came from the discovery of natural gas near the town of Groningen in 1956, which raised the real exchange rate of the Netherlands.

when high paying low skill jobs in the resource sector are on offer. A third possible causal channel of the resource curse is that dependency on natural resources can decrease the quality of a country's institutions, resulting in a weakening of economic outcomes. Some scholars such as Ross (2001) and Isham, et al. (2005) find that resource intensity can put downward pressure on institutional quality by providing governments with sources of revenue outside income taxes, and thus lessen their need for democratic accountability, and their vulnerability to demands for democratic reforms. Institutional effects are also supported empirically by Bulte, Damania, and Deacon (2005) who link resource abundance (measured as a share of resource exports in total exports) with less rule of law and less government effectiveness as evidenced by a corruption measure.

As mentioned, studies looking for a resource curse have now been conducted for over two decades, and have found various conclusions, and raised an extensive debate. As studies have accumulated, some economists have surveyed the literature, and mapped some important conclusions. For example, Cust and Poelhekke (2015a), Badeeb, Lean, and Clark (2017), and van der Ploeg and Poelhekke (2016) have documented that an inverse association between resource *dependence* (rather than abundance) and economic performance has commonly been found in cross-country macro-level studies. Some survey papers have blamed the literature's contradictory findings on weak robustness checks, unobserved heterogeneity across countries that affects their economic outcomes, and the possible endogeneity of many commonly used resource dependence measures.

For example, Van der Ploeg and Poelhekke (2016) criticize past cross-section and panel data analysis between countries. Firstly, Van der Ploeg and Poelhekke claim that international datasets on which most studies depend are commonly too diverse with respect to the characteristic of each country. Employing cross-country analyses can lead to serious omitted variable bias issues.[5] Second, they argue that endogeneity problems likely occur when researchers use common proxies for resource dependence such as the share of primary exports in total GDP. As a result, the actual effects of unmeasured factors on growth are wrongly loaded onto resource dependence, or there can be spurious negative correlation with outcome measures.

[5] They suggests that doing "old cross-country" analysis should be no longer chosen as a way to find an evidence of resource curse itself. See Van der Ploeg & Poelhekke (2016).

In their conclusion, Van der Ploeg and Poelhekke recommend researchers pursue new strategies and datasets to produce more reliable evidence regarding the resource curse. Especially relevant here, they suggest that within-country analysis which emphasizes a specific area in one country, or the local impact of resource intensity, may provide a more reliable test of the resource curse hypothesis. This recommendation has also been proposed in other recent surveys by Papyrakis (2016), Aragona, Chuhan-Pole, and Land (2015), Cust and Poelhekke (2015a). Papyrakis, for example, notes with approval that attention currently has shifted to analysis of data within countries at the district or county level to test the effects of natural resources. Papyrakis then argues that it is not enough to monitor macroeconomic outcomes, but that evidence of resource effects should be evident at the regional level. Further impetus for within country analysis is given by Aragon, Chuhan-Pole, and Land (2015), who emphasize the need to monitor local effects as many resource-rich countries have decentralized their fiscal systems. This decentralization has in some cases led to significant revenue windfalls for producer regions.

Many academics that have followed this advice have found a beneficial, rather than detrimental effect of resource intensity. Among within-country studies, for example, Caselli and Michaels (2013) assess the effect of resource windfalls at the local level in Brazil, and find a positive impact on incomes, local public goods, and public service delivery. A similar study of mining activities in 71 local government areas in Australia between 2006 and 2007 by Hajkowicz, Heyenga, & Moffat (2011) finds no negative effects on per capita GDP. Rather, Hajkowicz, Heyenga, & Moffat find that mining operations are positively correlated with income, as well as with selected quality of life indicators. The same conclusion is reached by Fan, Fang, & Park (2012) in the case of local level mining in China. Lastly, McMahon and Moreira (2014) also find no evidence of the resource curse when investigating the impact of the mining sector on social and economic development indicators in the five resource-rich mining countries of Chile, Ghana, Indonesia, Peru, and South Africa. McMahon and Moreira focused on these five nations because they have a history of substantial mining discoveries.[6]

Unfortunately, such within-country studies have not resolved the resource curse debate. Other within-country studies have found opposing results more in line with those of

[6] In this study McMahon and Moreira concentrate on low and middle income mining countries and find that mining has a strong positive impact on economic growth and on the Human Development Index (HDI). Unfortunately, the paper does not employ econometric analysis and therefore can not offer proof about any causal effects of mining revenues.

Sachs and Warner. Papyrakis and Gerlagh (2007), for instance, examine United States counties as a pooled cross section and find a negative cross-county association between resource dependence (measured as the share of the primary sector in the real gross state product (GSP)), and long-term income growth. Papyrakis and Gerlagh also claim that a resource curse can be found even in more homogenous sub-samples of counties. Similarly, James & Aadland (2011) confirm this view and find a negative effect of natural resources earnings on growth in income per capita in counties of the United States. These results are consistent with those of Douglas and Walker (2016) who find negative effects of resource-sector dependence when trying to investigate the coal mining effect among Appalachian counties in the United States. Douglas and Walker use a panel data set between 1970-2010 which is averaged over every 10 year period, or with four decade observations. Along with using fixed effects in their first analysis, these authors also use two-step GMM instrumental variables to address potential endogeneity in their resource measure.

Surprisingly, while numerous empirical resource curse studies have been carried out in the Middle East, Africa, and Latin America, this phenomenon has not been examined to nearly the same degree in Southeast Asia. Indonesia is the richest country in Southeast Asia in terms of natural resource endowments of all types (oil, natural gas, coal, minerals, forest products, and agriculture).[7] Yet resource abundance and dependence vary dramatically among regions of the country. Some prominent papers have included Indonesia as a sample country among other resource-rich countries (e.g. Gylfason (2001), Gylfason and Zoega (2006), Brunnschweiller and Bulte (2008), Arezki and van der Ploeg (2011)). However, there have been very few studies testing for a resource curse within Indonesia.

In pioneering work, Komarulzaman and Alisjahbana (2001) analyze the effect of resource rents (separated as forest, mining, oil and gas, and total resource rents) on the growth rate of district GDP, called real GRDP (Gross Regional Domestic Product) in 2001, the first year of Indonesia's fiscal decentralization. Edwards (2016) expands the investigation within Indonesia by focusing on the effect of mining dependence (the share of mining in total value-added) on several social development indicators (that include health and education), using cross-section data from the year 2009. However both studies have relied on single year cross-section data, making their conclusions vulnerable to omitted variable bias. More recently, Cust and Rusli (2015) have provided a valuable analysis of the

---

[7] Indonesia is currently 7th in total mineral production, and the largest coal exporter in the world in terms of value added or in government revenues generated by mining.

effects of district government revenues associated with petroleum royalties on district economic performance, proxied again by GRDP. Cust and Rusli's method seems to be promising as they have access to a longer period, 1999-2009, and consider effects of royalties on levels and changes in GRDP. Cust and Rusli also address the potential endogeneity of royalty revenues using total offshore oil and gas production as an instrumental variable in both level and change models. Dependence of local government revenues from petroleum royalties is, like most resource dependence or abundance measures, prone to endogeneity because of omitted variables that affect incomes or growth and because of spurious negative correlation where higher incomes simultaneously raise the dependent variable and the denominator of the resource measure. Cust and Rusli emphasize the importance of addressing the endogeneity issue that resource curse researchers face. Surprisingly, far from a resource curse, Cust and Rusli instead find that revenue windfalls boost local economic GRDP. Beyond these few papers, to the best of my knowledge, none has investigated the resource curse within Indonesia using sub-national data.

1.2 The Significance of the Research

The limited number of studies of the resource curse in Indonesia motivates me to test whether a curse phenomenon really exists when we can follow Indonesian districts over time. Therefore, this first part of my dissertation attempts to investigate empirically the overall effect of natural resources on economic performance within Indonesia at the sub-provincial level of districts. For reasons of data availability, I focus here on all non-renewable "point source" resources, namely oil, natural gas and coal. I focus on resource dependence measures, either the share of resources in district GRDP, or the share of 'windfall' revenues that district governments receive as a share of their total budgets. I consider the years following the implementation of fiscal decentralization, from 2005 to 2015. Finally, I construct and exploit various instrumental variables for resource dependence by introducing "historical resource abundance" measures available 30 years prior to decentralization.

As mentioned above, I focus on mining in Indonesia, employing the main resource intensity variables of "mining dependence" and "mining revenue dependence" on sub-provincial level economic performance across all districts in Indonesia.[8] I consider the post-decentralization period of the Indonesian economy, where much decision-making power and revenues devolved from the central government to provinces and districts. According to the Indonesian Ministry of Home Affairs, in 2015, there were 512 districts within 34 provinces in Indonesia. Since decentralization began in 2001, the Indonesia government has pursued a policy called "proliferation" or *pemekaran*. This policy has expanded the number of districts continuously. In 2001, there were just 336 districts, rising to 477 in 2010, and 512 in 2015. This proliferation of districts poses some challenges for any local level analysis that follows districts over time.

The rest of this first part of my dissertation will proceed as follows: Section 2 reviews the resource curse literature, including both its theories and empirical tests. I pay particular attention to those studies concerned with within-country estimation of resource effects. Section 3 emphasizes the historical aspects and the role of natural resources in Indonesia, and describes that country's substantial policy changes during the period of decentralization begun in 2001. Section 4 explains the data, and my empirical estimation strategies for estimating direct and indirect effects of mining dependence. Section 5 discusses the results of my analysis. Finally, Section 6 concludes the chapter and sets the ground for those that follow.

2 Literature Review

2.1 Natural Resources and Economic Development

Natural resources have been recognized as a key factor in the economic progress of many nations. Walter Rostow an American economist and political theorist at Columbia University argued that natural resources act as a preliminary foundation for many countries' "take off" into industrialization. Barbier (2005), a development economist, in his book *Natural Resources and Economic Development* argues that this transition phase, "in which countries achieve rapid development" is often driven by access to abundant natural resources, and in particular the discovery of new sources of raw materials. Barbier argues that the term "resource-based development", which has been applied to some well known

[8] Mining here is defined according to International Standard Classification 0509, and comprises natural gas, coal, lignite, crude petroleum and other minerals. The definition follows that used in the recent study by Edwards (2016). Under its decentralization scheme, Indonesia has 34 provinces and (in 2015) consists of 512 districts. Since each district publishes information on gross domestic output value [real and nominal price] by sector and in total, I can calculate resource dependence by dividing mining output by total output.

countries that have been leaders in the world economy, is itself evidence of the influence of natural resource endowments in every stage of economic expansion.

Looking at broad swathes of history, Barbier summarizes several phases in which natural resources have contributed to stages of past human civilization. The first stage, *the agricultural transition*, occured between 8,500 BC to 1 AD, and is characterised as a period when society, either tribes or individuals within society, compete with each other in hunting or planting something on the earth to gain benefit from natural resources, often simply for survival. Barbier calls the second stage, *the era of Malthusian stagnation* (from 1 AD to 1,000 AD); natural resources determined food sufficiency and economic stability in human civilization. The third stage he calls *the emergence of the world economy*, between 1,000 and 1,500 AD, when international trade in renewable and non-renewable raw materials vastly expanded between nations.

Barbier labels the next historical period *the rise of Western Europe* (between the 1500-1913). During this period, many West European countries created colonies in many parts of Africa, Asia and Latin America. These efforts were largely driven by the desire to access quantities of natural resources from these countries and regions. Colonization also occured in North America where two countries, the United States and Canada, became influential in the world economy. Barbier divides this period between *Atlantic economic triangular trade* (between 1500 and 1860), where trade aggreements between countries were formalized, and the later *golden age of resource-based development* (from 1870 to 1913).

Wright and Czelusta (2004), who also take a long historical view, argue that a number of successfully developed countries achieved that success with resource based development that was inevitably driven by the influence of natural resources. Wright and Czelusta emphasize the contribution of mineral production, which had strong linkages with advancing technology. Mineral production provided substantial benefits to countries such as the United States and Australia. Doraisami (2015) also argues that substantial knowledge spillovers resulted from the linkages between nations' extractive sectors and industrialization, which in turn has driven successful development.

The link between natural resources and economic output is commonly approached using a basic Cobb-Douglas technology function in which natural resources are involved as an substantial determinant of a nation's aggregate output.[9] In a growth literature that has developed since Rostow, natural resources are also commonly seen as a part of nation's capital stock K. As one example, Lederman and Maloney (2008) model output assuming that (K) consists of resource endowments, which are used either in static or dynamic growth models.[10]

However, regardless of historians' assertions of a positive effect of natural resources on development, the first empirical study found a famously contrarian result. Sachs and Warners (1995) were the first authors to find empirical evidence for a "resource curse". Empirically, Sachs and Warner find that countries that depended largely on resource exports (measured as the ratio of primary product exports to GDP in 1970) experienced slower economic growth in subsequent periods (measured as the average of 1971-1989). Several causal channels have been proposed to explain why an abundance of natural resources can become a curse (or a blessing) for a society. I concentrate here on four channels that have received dominant attention in many papers: (1) the Dutch disease; (2) effects on human capital, (3) effects on institutional quality, and, (4) effects on the quality of government investment/spending. These will be explored in depth in Chapter II, but I will give here a short summary.

The Dutch disease was first introduced in the *Economist* magazine inspired by the discovery of natural gas in Groningen, the Netherlands in the late 1950's (Frankel 2010). As documented by Davis (1995), the resulting explosion of mining in Gronigen led to an appreciation of the Dutch Guilder, which in turn decreased world demand for the export of non-resource tradable sectors such as manufacturing and agriculture. This phenomenon was one of the first causal explanations for resource endowments bringing a curse, rather than a blessing.[11]

The next causal mechanism for a curse is through education. Gylfason (2001) and Gylfason and Zoega (2006) have pointed out that natural resource dependence may reduce demand side incentives for human capital accumulation. This may be observed as a

---

[9] Stiglitz (1974) includes the rate of natural resources utilization in the form of Cobb-Douglas technology, $Q = F(K, L, R, t) = K^{\alpha_1} L^{\alpha_2} R^{\alpha_3} e^{\gamma t}, \quad \alpha_1 + \alpha_2 + \alpha_3 = 1$. Here Q is a nation's aggregate output, R is its rate of use of natural resources, L represents its supply of labor, and K and γ stand for its capital stock and rate of technological progress, respectively.

[10] Brief explanation see Lederman and Maloney (2008), "In Search of the Missing Resource Curse".

[11] Aragon, Chuhan-Pole and Land (2015) comment that the Dutch disease is analogous to deindustrialization driven by resource windfalls.

decrease in school enrollment, public expenditures on education, or expected years of schooling in more resource intensive societies (Gylfason, Herbertsson and Zoega, 1999). Yet conversely, resource revenues could increase state funding for the supply of public education.

Third, most empirical studies also predict that a resource curse is a phenomenon closely related to institutional quality. There are two variants of this argument: (a) Institutional quality is an endogenous factor, negatively affected by resource abundance/dependence, which in turn worsens economic performance. (b) Institutional quality is asummed to be exogenous to resource intensity, but that quality largely determines whether resources are a curse or blessing.[12]

The fourth channel relates to the quality of public spending that results from resource vs non-resource sources of government revenues. A curse could result if windfall government revenues would be less likely to be spent on investment than non-resource revenues, such as income or consumption tax revenues. This argument often interacts with decentralization of revenues and responsibility for public good investment and provision, such as that which has taken place in Indonesia.

Under decentralization, resource extraction activities operate in local areas and the revenues are managed by the central government. However, the central government transfers resource rents back to the producing districts. Cust and Poelhekke (2015a) and Aragon, Chuhan-Pole, and Land (2015) both emphasize this link between resource effects, government funding source, and quality of expenditures.

2.2 The Resource Curse: A Survey of Empirical Studies

Sachs and Warner's influential study brought much attention from scholars because the authors concluded that resource-rich economies experience slower economic growth than resource-scarce economies, other things equal. In particular, Sachs and Warner (1995, 1999) find that "resource abundance", which they defined as each country's share of primary exports (SXP) in total GDP, has on average a negative association with average growth in single year or pooled cross-section regressions.

[12] Mehlum, Moene, and Torvik (2006) distinguish two alternative types of institutions: "grabber friendly" and "producer friendly".

This surprising result was found also by subsequent studies (e.g. Gylfason, 2001; Stijns (2000), Papyrakis & Gerlagh, 2003, Mehlum & Torvik, 2006). However, other studies began pointing to weaknesses of Sachs and Warner's methods. For example, Brunnschweiller and Bulte (2008) criticize Sachs and Warner's resource "abundance" as actually defining its degree of dependence on resources.[13] Brunnschweiller and Bulte distinguish resource abundance as a country's *stock* of natural resource wealth, whereas resource dependence is the proportion of the *flow* of income that a country receives from natural resources. These authors find that resource abundance is *positively* correlated with economic growth and with institutional quality.[14] More specifically, Brunschweiler and Bulte argue that resource abundance positively affects resource dependence, and that Sachs and Warner's resource de facto dependence measure (the ratio of resource exports over GDP) suffers from endogeneity. To address this, Brunnschweiller and Bulte instrument this dependence using averaged *historical openness* to trade between 1950-1969, but still find no evidence that higher dependence lowers economic growth.

Other researchers have taken issue with the possible omitted variable bias of Sachs and Warner's cross-section analysis. Lederman and Maloney (2003) update Sachs and Warner's paper by performing both cross-section and panel fixed effects to compare the results. Their panel regression models find a positive effect of resource dependence on GDP per capita, whereas cross-section models find no significant association. Alexeev and Conrad (2009) also use country fixed effects, and find when using large oil endowments as an abundance measure that resource-rich countries experience higher growth in GDP per capita growth.

Yet other researchers argue that Sachs and Warner specifically neglected to control for institutional quality. Mehlum, Moene and Torvik (2006) argue that the curse effect is conditionally driven by the (exogenous) quality of countries' institutions. At first, these authors show that inferior institutions lead to a curse. Instead of following the rent seeking hypothesis, which treats institutions as endogenously affected by resource dependence,

[13] Other authors also expressed doubts about Sachs and Warner's measurement. For example Aleexev and Conrad (2016) tried several other measures of resource abudance such as resource deposits per capita or oil and mining production, and find no adverse effect.

[14] In general there is now a consensus that resource abundance represents the stock under the land of resources deposits or reserves while resource dependence is the flow of natural resources. Thus, natural resource abundance tends to be measured by using "stock" measures of estimated deposits in the ground. As an example, Brunnschweiler and Bulte (2008) use each nation's total amount of sub-soil wealth to measure natural resource abundance.

these authors treat institutional factors exogeneously, but use Sachs and Warner's data.[15] They find that when institutional quality is controlled for within the Sachs and Warner model or interacted with the natural resource dependence measure, the negative effect of dependence on GDP growth vanishes in countries with "producer friendly" institutions, while remaining for countries with " grabber friendly" institutions.

Other researchers, such as Arezki and van der Ploeg (2011), take issue specifically with a potential negative spurious correlation that may arise when researchers such as Sachs and Warner place GDP both as the dependent variable, and as the denominator of the right hand side dependence measure. For example, countries experiencing strong non-resource growth would appear to have a negative association between growth in "resource dependence" and in growth in GDP. Van der Ploeg (2011) also notes that cross-section analysis is highly prone to omitted variable bias. Some other recent papers have also tried to focus on dependence measures yet to address potential endogeneity, and again found contrarian positive results. Ouoba (2016) for example, finds positive and significant effects when he tries to use Sachs and Warner's measure: resource dependence in GDP using a sample of resource-rich countries. Ouba compares results from different techniques such as Driscoll-Kraay Fixed Effects, Instrumental Variables with 2SLS, and a GMM-System estimator following countries between 1980-2010. Similarly, Bjorvatn, Farzanegan, and Schneider (2012), using 30 oil-rich countries between 1993-2005 find positive effects of oil revenues on real GDP per capita (in logs).

More recently, Aragon, Chuhan-Pole, and Land (2015) emphasize that it is difficult to generalize the effect of natural resources (positive or negative) at the broad national level. Aragon, Chuhan-Pole, and Land argue that any potential resource curse effect will be a local phenomenon, more suitable to analyze at a more local (sub-national) geographic level. In other words, they imply that a resource effect will be difficult to identify using cross-country variation.

Thus, while most early resource curse tests were cross-country, mixed findings and concerns over omitted variables that affect growth have resulted in a recent shift towards within-country studies. Cust & Poelhekke (2015), Aragon, Chuhan-Pole, and Land (2015) and Van der Ploeg & Poelhekke (2016) have all recommended that researchers look for

---

[15] Mehlum and Torvik use Sachs and Warner's data which have been published in a *Journal of African Economies* article.

resource effects using within country analysis.[16] Cust and Poelhekke in particular highlight the urgency of narrowing down the investigation of the resource curse to regional development dynamics within specific countries. In a more recent survey article, Badeeb, Lean and Clark (2017) conclude that moving particular attention to within country studies and using more recent data after 2000 is crucial as many resource curse studies have been based on data from the 1990's, with limited variation in resource price movements.

However, even within the confines of within-country analysis, different results still occur, which makes it difficult to reach a general consensus regarding whether resource dependence is a curse or a blessing. For example, Douglas and Walker (2016) conduct an analysis on the effects of coal dependence at the county level in the Appalachian region of the United States. Douglas and Walker use the period 1970 – 2010 for their analysis, and estimate that an increase of coal mining dependence lowers the annual growth rate of per capita income by roughly 0.5-1.0 percentage points in the long run, and by 0.2 percentage points in the short run. Douglas and Walker thus seem to confirm Sachs and Warner's cross-country findings. Guo, Zheng, and Song (2016) similarly find negative, albeit weak linkages between resource dependence and output using panel data at the provinvial level in China. In contrast, other within-country studies find positive effects of resource dependence, such as Hajkowich, Heyenga and Moffat (2011) and Fleming & Measham (2015) for Australia, Weber (2012, 2014) for Western U.S. states, Libman (2013) for Russia, Aragón and Rud (2013) for the case of Northern Peru, and most relevant for our purposes, Cust and Rusli (2016) for Indonesia (see Appendix 5 for a summary of some blessing effect results).

Weber (2012, 2014), for example, focuses on the South-Central United States, and maps 362 non-metropolitan counties in Arkansas, Lousiana, Oklahoma, and Texas, and finds that natural gas development (defined as the change in natural gas production in billions of cubic feet) has a positive effect on total employment, using a first difference method. Specifically, Weber finds that each gas-related mining job is likely to create 1.4 non-mining jobs for the local area. Boyce and Emery (2011) also find a positive effect when regressing the share of people employed in natural resource industries on income levels using US state level data.

[16] Explicitly, these authors accept that within-country studies provide a better identification strategy, Also add that a positive impact on growth has been found by those within-country studies previously done. (Cust and Poelhekke (2015), Aragon, Chuhan-Pole and Land (2015))

To summarise, the standard resource curse hypothesis has postulated that countries endowed with abundant natural resources grow slower than countries without such endowments. However, empirical findings have been mixed, and striking counter examples exist.

2.3 The Resource Curse in Asia and Southeast Asia

Very few empirical studies have tried to examine the effect of natural resources on economic growth in Southeast Asia.[17] A greater number have examined the resource curse in East Asia, in China in particular (see Fan, Yang and Park (2012); Lei, Cui, & Pan (2013); Wu & Lei (2016), Zhuang & Zhang (2016). These do not tend to find strong evidence of a curse using sub-national data (e.g. Fan, Yang and Park (2012) using city level data).

For Southeast Asia as a whole, Sovacool (2010) examines evidence for the resource curse by quantifying some key indicators without using econometrics analysis, and draws the opposite conclusion from a resource curse prediction. He chooses thirteen dimensions of outcome variables to represent all aspects of development, arguing that a single indicator such as economic growth (in GDP per capita) is inadequate to capture complex relationships between resource intensity and development.

Specifically, Sovacool combines six economic factors (gross domestic product, exports, government revenues, per capita income, inflation and poverty levels), political factors (including measures of transparency and natural gas and oil production), and four social indicators (rates of literacy, infant mortality, undernourishment, and life expectancy). Sovacool concludes that Southeast Asian countries, with the exception of Myanmar, are able to avoid the curse. Even the more resource dependent countries achieve good progress in most indicators. By comparing outcomes against those of major Middle Eastern oil and gas countries, who are members of OPEC, Sovacool finds that Southeast Asia has performed much better.

In similarly descriptive work, Coxhead (2007) identifies Indonesia, Malaysia and Thailand as resource abundant countries which managed their economies very well between 1975-2001. The average rate of GDP growth in these three countries was above the overall

[17] This comprises of ten countries which are currently playing an important role in the world economy. Indonesia, Thailand, Malaysia, Singapore, Cambodia, Vietnam, Myanmar, Lao PDR and Brunei Darussalam.

mean of all countries in Southeast Asia. Coxhead argues that a massive flow of foreign direct investment (FDI) between 1985 and 1991 was the key factor which raised industrialization rates for these three countries. As a consequence of this remarkable achievement, the World Bank has grouped these countries as a new “East Asian miracle” alongside Singapore and some other Northeast Asian economies.

2.4 Empirical Evidence Related to the Resource Curse in Indonesia

Moving to Indonesia in particular, there have been only a small number of empirical studies looking within that country, even though many cross-country studies have included Indonesia as a resource-intensive data point.

A few studies have discussed Indonesia and the resource curse in a very descriptive way, such as Usui (1997), Rosser (2007), and Chandra (2012). Usui (1997) claims that Indonesia has successfully escaped relatively unscathed from both the Dutch disease in times of rising oil prices and from later declining oil prices, over the combined period from the 1980’s to the 2000’s. Usui argues that good policy adjustments have contributed to the Dutch disease being avoided. Similarly, Gylfason (2001a) places Indonesia alongside Bostwana, Malaysia and Thailand among 65 countries that have successfully managed long term investment, making their economic growth exceed 4 percent on average between 1970-1998. Gylfason argues generally that diversification and industrialization have helped them reach that level of growth.

Rosser (2007), similarly, describes Indonesia’s economy during a period of intermittent oil booms between 1967-2000. Qualitatively, Rosser argues that the oil booms did not carry Indonesia into “curse” conditions. Instead, the country experienced strong growth in the 1970’s and 1980’s in a more sustained pattern than other Southeast Asian countries. Rosser credits this growth in part to political factors such as a successful transition of power (from the old order, under Soekarno’s rule (1945-1966), to Soeharto’s new order (1966-1998)), and to favourable external economic conditions. Again talking a descriptive approach, di John (2011) identifies Mexico and Indonesia alone among the ten largest oil exporters as having succesfully managed their growth during oil price booms by introducing a “Dual track strategy”. These two countries translated oil windfalls between 1981-2002 into domestic investment to build and accelerate industrialization.

Finally among descriptive works, Chandra (2012) considers the effects of oil price booms on Indonesia's overall economic growth over a longer period. Chandra finds that Indonesia, especially in the 1970's-1980's successfully managed the revenue windfall that came from massive mineral exports, especially oil and gas, to build their manufacturing sector. By the 1990's, much of overall growth nationally was driven by manufacturing performance, though in the 2000's it was driven by growth in both the primary and manufacturing sectors. Chandra also notes that although Indonesia experienced oil price volatility in the early 1980's, the country did not suffer a resource curse generally, nor a Dutch disease in particular. Instead, Indonesia was able to use revenue windfalls to develop their manufacturing sector. By the time of declining global commodity prices in the 2000's, falling windfall revenues did not much affect the industrialization process. However, although Chandra's study is fairly comprehensive in the time period it considers, it is purely descriptive, and only considers overall macroeconomic conditions.

While previous studies have generally argued that Indonesia has avoided a resource curse, few have looked for evidence of resource intensity effects within the country, using district level data, in the period following decentralization. Prior to decentralization, during the Soeharto era, Indonesia experienced good progress in terms of key macro-economic indicators. However, the authoritarian governance under Soeharto, while sometimes good for political stability, hampered democracy and increased scope for rent-seeking behaviour among the elites with ties to the government. When the Asian Financial Crisis struck several Southeast Asian countries in 1997, Indonesia's economy performed particularly badly, making Soeharto step down and paving the way for a change from a highly centralized administration to a decentralized and democratically accountable system of provincial and district level governance.[18]

Under decentralization, all provinces and districts receive a certain amount of revenue based on a legal scheme of "resource revenue-sharing".[19] In general, the higher the revenues generated from resource endowments within a district, the higher the revenues it receives back into its budget every year. The revenue-sharing schemes known as

[18] In the post Soeharto era, Indonesia adopted a decentralization system, with legal changes beginning in 2001, and political implementation beginning in 2005.

[19] Aragon, Chuhan-Pole and Land (2015) explain that fiscal decentralization arrangements provide policies to answer three questions: (1) who should collect revenues (local, regional, or national governments)?; (2) How will resource revenues be shared?; and (3) how these institutional arrangements affect economic performance.

"intergovernmental transfers" in Law 33/2004, are calculated based on percentage allocations (see Table 1).

Hill, Resosudarmo, and Vidyattama (2008) were the first researchers to rigorously evaluate Indonesia's development progress at the provincial level over three decades from 1980-2010. They cover the years before and after decentralization of funds and decision making to provinces and districts. Although still at the somewhat broad provincial level, which can contain strong variation in district government performance, Hill, et al. find some indication that income growth in Indonesia was relatively strong and stable over this thirty year period. They also find that those provinces situated on the islands of Kalimantan and Sumatra were consistently among the richest (proxied by per capita GRDP) and their relative standing remained unchanged between 1999 and 2011.

The first econometric analysis of the resource curse in Indonesia was conducted by Komarulzaman and Alisjahbana (2006). These authors use about 300 districts that existed in 2001. Komarulzaman and Alisjahbana consider the effects of four measures of natural resource rents, measured using district-level resource revenues: (i) forestry revenue; (ii) mining revenue (land rents and royalties from coal and other minerals); (iii) oil and gas revenue; and (iv) total resource revenues (total rent). They find that while total revenue (from all natural resources) has no significant impact on regional economic growth, mining sector revenues are negatively associated with economic growth on average. However, Komarulzaman and Alisjahbana's study is based on a single year cross section analysis, in the earliest period of decentralization when many districts had not long been receiving resource funds.

Edwards (2016) offers more recent evidence regarding Indonesia's natural resources, albeit not exactly as a resource curse investigation (i.e. not using per capita GDP levels or growth as a dependent variable). Instead, Edwards performs cross-section analysis of more than 430 local districts in Indonesia in 2009, looking at the effect of mining dependence, (proxied using all types of non-renewable resource output over total output at the district level), on various important development indicators. Interestingly when using mining share in GRDP (in log form), Edwards concludes that mining dependence may significantly reduce household human capital investment (measured using education and health expenditures). Mining dependence may also reduce education and health outcomes, which are proxied using senior secondary school enrollment, senior test scores, and births attended by a skilled health worker, respectively. However, Edwards does not use instrumental variables to address potential endogeneity in his resource dependence measure.

Edwards' findings may provide initial evidence of a resource curse within Indonesia. However, similar to Komarulzaman and Alisjahbana, Edwards' analysis covers a single year (2009), and focuses only on social development indicators (health and education). Conversely, Komarulzaman and Alisjahbana's study has the advantage of considering economic performance as a dependent variable, but their study does not follow districts over the period when decentralization of revenues to districts and political decentralization to local citizens were fully implemented. To sum up, there is as yet no clear evidence regarding whether heavy reliance upon resources consitutes a blessing or curse for Indonesia.

The study closest to my own investigation is by Cust and Rusli (2016). Cust and Rusli examine the effects of oil and gas dependence on levels or growth in Indonesian district GRDP between 1999 and 2009. Cust and Rusli also address the potential endogeneity of their oil and gas dependence variable by using the instrument of physical offshore oil production (within 0 – 4 miles of the coastline). Taking this more comprehensive approach, Cust and Rusli find a surprising positive, statistically significant effect of oil and gas dependence upon district GRDP using either levels or changes between 1999 and 2009.

While Cust and Rusli's study provides the highest quality investigation of the resource curse within Indonesia to date, my current investigation contributes on several fronts. First, I start my analysis several years later, when district level data reporting capacity had improved post-decentralization, and I extend analysis to more recent years – 2015. Second, I examine the effects of coal dependence as well as oil and gas. Third, while repeating Cust and Rusli's use of physical output instruments, I also source other instruments related to historical resource abundance – a necessary precondition for resource dependence.

3 A Glimpse of Indonesia's Natural Resources History

Indonesia has a very long history of natural resource exploration. Many ventures were initiated by Dutch geologists, when the Netherlands colonized Indonesia on behalf of the *Netherlands East Indies* company. The petroleum history of Indonesia began in 1871 when Jan Reerink, a Dutch geologist surveyed and drilled at several locations in Tjibodas (now

Cirebon district) in West Java Province in search of crude oil. Though Reerink eventually found oil, Tjibodas failed to provide sufficient quantities of production to be commercialized. While Reerink and others made further attempts in some nominated areas, these also were unsuccessful in extracting substantial amounts of oil. Nonetheless, these efforts left some legacies as a clue to the location of oil deposits over West Java and some others islands in Indonesia.[20]

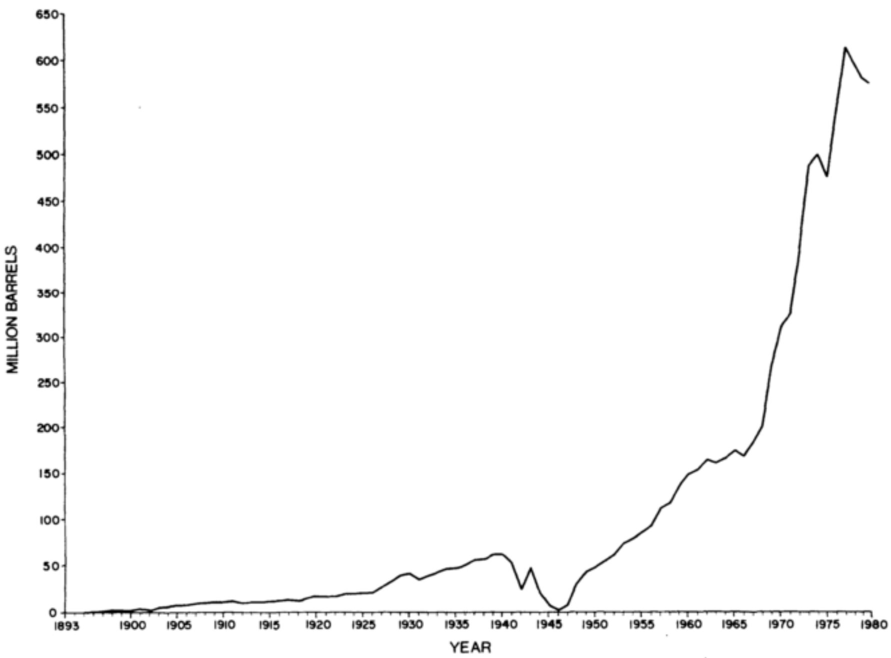
In 1911, the well known Dutch company Royal Dutch (also known as *Bataafsche Petroleum Maatschappij* or B.P.M) found strong evidence of large deposits of crude oil on several islands[21]. As a result, Royal Dutch secured roughly 44 concessions of oil fields, spread over Sumatra, Kalimantan and Java Islands, which succeeded in producing around 13 million barrels. The *Nederlandsche Koloniale Petroleum Maatscappij* (N.K.P.M) then began exploration in 1912 as a competitor to Royal Dutch, but its concession was limited to operating in the Talang Akar area of South Sumatra so that its production was limited. By 1930, the main fields of oil on Kalimantan Island contributing about 68 per cent of Indonesia total oil production. More specifically, East Kalimantan and North-East Kalimantan Provinces were the largest contributors by the late 1920's.

Caltex, a merger between *Nederlandsche Pacific Petroleum Maatschappij* (a subsidiary of Standard Oil of California) and the Texas Corporation operated in Indonesia starting in 1936. Caltex made many succesful explorations and commercialization of oil production. Its exploration was concentrated in the Minas Field of Central Sumatra, and by 1940 wells there were contributing about 61.5 million barrels annually (Bee, 1982). Unfortunately, oil production fluctuated and fell dramatically because of the Second World War. Indonesia was targeted by Japan for occupation in large part because of the country's vast deposits of natural resources. Many Dutch concessions were overtaken by the Japanese. At the war's end when Japan surrendered to the United States in August 1945, the young Indonesian leader Soekarno took the opportunity to proclaim Indonesia's independence, though the Dutch government did not acknowledge Indonesia's proclamation. It failed, however, to regain the country using aggression or political negotiation.

[20] The historical perspective here heavily cites from Bee (1982).
[21] Also known as *Bataafsche Petroleum Maatscappij (B.P.M)*

During Soekarno's rule of Indonesia, the country adapted a nationalization policy of the oil and gas sector. The Indonesia Oil Company took what had been left by Royal Dutch (BPM), Shell, and other companies. Under the Indonesia Oil Company, the rate of production rose from 63 million barrels in 1951 to about 177 million barrels by 1965. However, a coup attempt by the Communist Party in 1965 destabilized the goverment. Soekarno was accused of protecting communist ideology, lost his power, and his old order of government collapsed. Major General Soeharto, who had been supported by the Indonesian military, became the new leader in 1966, and ruled Indonesia until 1998. While authoritarian, the political situation stabilized, and foreign investment was encouraged as a result of a liberalization policy pursued by Soeharto's cabinet.

Figure 1. Crude Oil Production in Indonesia, 1895-1980



Source: Bee (1982), page 15.

The renamed National Oil Company (PERTAMINA) attracted many foreign oil companies to join under "production sharing contracts" to explore and produce crude oil. This strategy was chosen both to share the cost of exploration, and to gain from foreign companies their capital and experience with advanced technology. As a result, many oil discoveries took place beginning in 1968, and resulted in several offshore oil fields, such as Cinta (North-West Java) and Attakka (East Kalimantan), along with the onshore Minas field in Central Sumatra. Crude oil production thus increased sharply in Indonesia between 1960-1980 (see Figure 1). While less prominent than oil, natural gas extraction also climbed rapidly in Indonesia, starting in 1976. The Arun and Badak fields in the Aceh Utara and Kutai districts, contributed to commercializing Indonesia's natural gas production for export across the world (Bee, 1982).

While crude oil has been the dominant non-renewable resource exploited in Indonesia, coal mining also has a long history. Initially, in the 1850's, geologists of the Dutch colonial government struggled to find coal abundant areas, with little attention paid thereafter. But after Soeharto ruled, coal exploration expanded quickly in the late 1970's, driven by the falling price of oil. Following this momentum, an important coal deposit was found in South Sumatra Basin (in the Tanjung Enim and West Banko districts) between 1973-1980, under the supervision of the state owned mining company *PN Tambang Batu Bara*.[22] Following this discovery, a golden period of coal extraction began between 1981-1988. This accelerated after the Indonesian government again invited several foreign companies who had successfully found the deposit, to sign a mining contract known as the first generation of Coal Contracts of Work (CCoW). Much of the country's subsequent coal production was sourced from these locations. In particular, those contracts signed between 1981 and 1990 contributed more than 50 percent of total coal output in 2015. All contracts were located on Kalimantan Island (in East and South Kalimantan Provinces) and in West Sumatra Provinces ((Leeuwen (1994) and Friederich and van Leeuwen (2017)).[23]

Moving to the more recent development of Indonesia's natural resources, Figure 2 shows the production of all types of natural resources in Indonesia over the 1973-2012 period. As shown, oil and coal have comprised more than 60 percent of total natural resource production in Indonesia. Crude oil, as already indicated has been a major contributor to Indonesia's resource economy from the 1970's to the 2000's but it subsequently experienced a slight decline relative to coal following the rising world prices of coal. As a result, oil remains the largest contributor to mining production in Indonesia, but coal production has risen dramatically to become the second largest resource contributor. Curiously, even though natural gas has been extracted since 1976, its

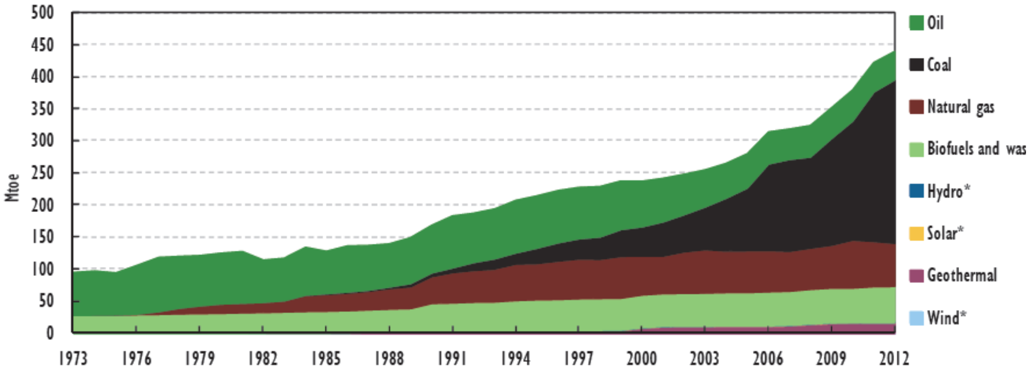
---

[22] These historical locations of oil, gas and coal in Indonesia have become the main areas of mineral extraction up to the present time. Kalimantan and Sumatra are the main locations.

[23] There were eleven foreign companies under contract with the Indonesia government under PN Tambang: Arutmin, Utah Indonesia, Agip, Kaltim Prima Cola, Adaro, Kideco, Berau, Chung Hua, Allied Indo Coal, Multi Harapan Utama, Tanito Harum, and Indominco Mandiri (Friederich and Leeuwen, 2017).

production has remained below 100 Mtoe over the 1976-2012 period. Growth in natural gas extraction has thus been very slow.

Figure 2. Production of mining in Indonesia, specified by types, 1973-2012



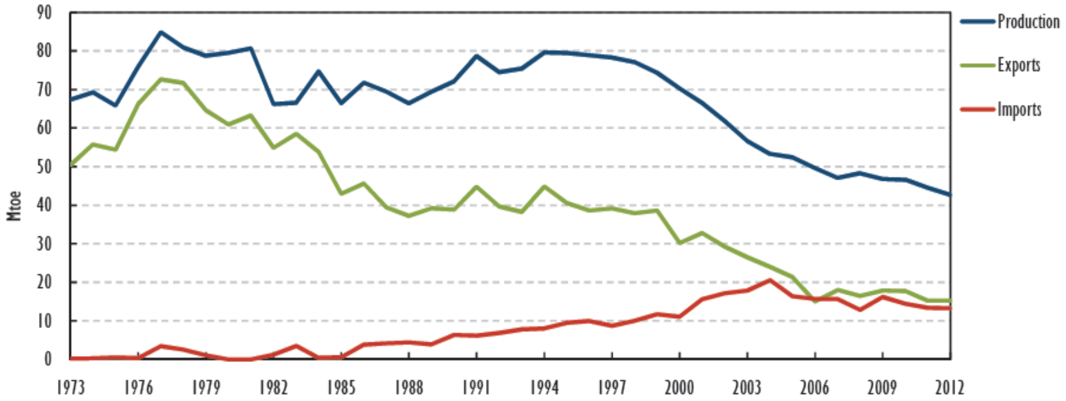
Source: IEA, Indonesia Energy Policies, 2015 (http://www.iea.org/publications/freepublications/publication/energy-policies-beyond-iea-countries---indonesia-2015.html)

Most recently, however, the production of natural gas has increased rapidly after the Indonesia government in 2009 launched a conversion program from kerosene to LPG (Liquified Petroleum Gas). Finally, the remaining types of resources aside from oil, gas and coal have not contributed very much.

While the production of crude oil has been large on average (as shown in Figure 2), annual production and exports rose from 1973-1976, cycled and then declined in a second phase from the mid 1990's to 2012. Production peaked about 80 Mtoe (one million tonne of oil equivalent) in 1994, before declining subsequently. This decline has been attributed to an excess global supply of crude oil, and a weakening demand for crude oil within European and Asian countries. Another factor has been the rise in LPG utilization, and to a lesser extent, attempts to develop non-fuel energy sources such as biofuels, geothermal, and hydro.

Export trends followed those in production, with a more pronounced decline since 1976, accompanied by an increase in the level of oil imports. Indeed imports reached the level of exports from 2003 to 2012.

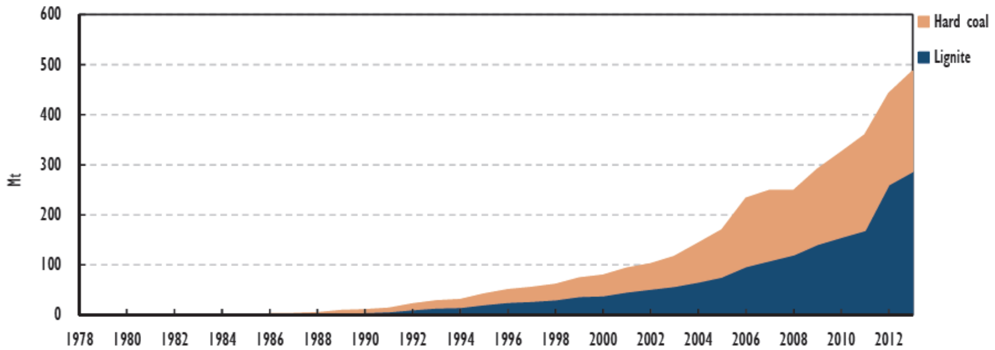
Figure 3. Production of crude oil in Indonesia, with export and import trend information, 1973-2012



Notes: Mtoe = million tonnes of oil-equivalent, Source: IEA, Indonesia Energy Policies, 2015

In contrast to oil, a rapid expansion of coal production occured in 2000 and continued until 2012 (see Figure 4). This rapid expansion has been driven by the high global demand for coal in China, India, and in some parts of Europe. As explained in Section 3, coal deposits were concentrated mostly in Kalimantan and Sumatra Islands where now East Kalimantan and South Sumatra Provinces have become the largest extraction areas. The major coal companies have operated in these areas for more than 25 years.

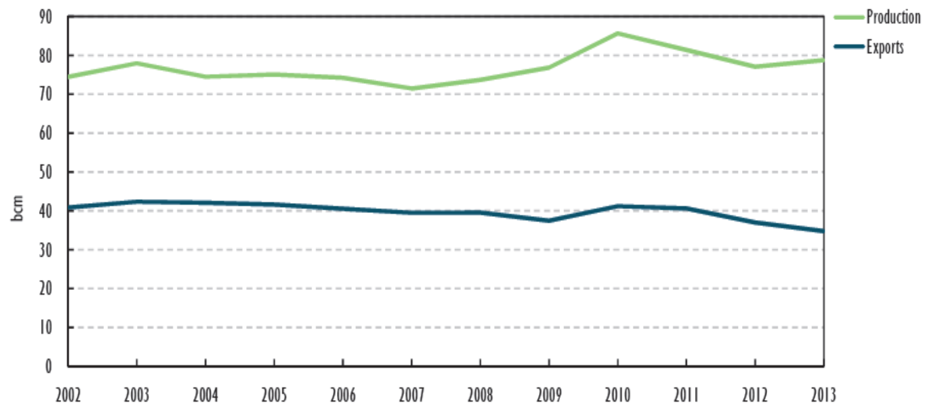
Figure 4. Production of coal in Indonesia, 1978-2012



Notes: Mt = metric ton
Source: IEA, Indonesia Energy Policies, 2015

While natural gas was developed in the same period in which oil extraction expanded and commercialized, its production remained stable over time. As shown in Figure 5, the rate of natural gas exports has been roughly half that of production levels, stabilising before decreasing slightly between 2011 and 2013.

Figure 5. Production of natural gas in Indonesia, 2002-2013



Notes: bcm = billion cubic metres
Source: IEA, Indonesia Energy Policies, 2015

4 Overview of the Natural Resource Policy Before and After the Decentralization Period

Indonesia is the third most populous country in the world after China and India. In Southeast Asia, according to data from the Association of Southeast Asian Nations (ASEAN)[24], Indonesia is the largest in terms of total land area (1,913,579 square kilometres), total population (255,461,700) and gross domestic product (more than 800 US$ million).

Decentralization began in Indonesia in 1999, when the autonomy law (Law 21/1999) was implemented. Most districts applied by 2001 to be both responsible for public service delivery for their local citizens, and to receive enabling financing from the central government.[25] Outside some more developed districts on Java Island, many districts previously had limited local taxation capacity. Thus, natural resource income became a fundamental source of finance for their spending (Aden (2001)).

Long before decentralization was implemented, Indonesia's main constitution (Law 1945) adopted a nationalistic and anti-liberalization ideology. With regards to natural

[24] Key Selected Indicators data base as announced in August 2016
[25] In 1999, the Indonesian central government initially announced Law 25/1999 regarding revenue sharing with districts from natural resources (oil, natural gas, coal and other minerals, forestry, fisheries resources management). Revenues were first to be collected by the central government and then re-distributed to the local level governments. But the initial regulation was incomplete, and a revised Law 33/2004 was substituted for the previous law.

resources management, Article 33 states that: "*The earth and water and the natural resources contained within them are to be controlled by the state and used for the greatest possible prosperity of the people*." However, the new order, under the Soeharto government was far more permissive in welcoming foreign investment, particularly in the extractive sector, and based upon "production sharing contracts". The Indonesian government assumed that these "partnerships" would be mutually benefitial.

Realizing that Indonesia was a large, diverse archipelago country, new government orders under Soeharto (Law 5/1974) sought to minimize the frictions within or between districts and to advance the country's development. Thus under Law 5/1974 the central government fully retained all administrative, political, and fiscal duties, reinforcing Soeharto's authoritarian style of leadership. As explained in theprevious section, this relationship changed rapidly in 1999 due to widespread demands for reformation. These changes produced laws that specified how revenue was to be shared, including natural resource revenues.

In essence, under the revised Law 33/2004, revenues from oil and gas wells are allocated to the district in which the *wellhead* has produced oil and gas (defined as 'lifting'). If the wellhead is situated on the district's land it is labelled as an *onshore* location; if it is *offshore*, the nearest distance to the coastline determines the district to whom the revenue is allocated. If the distance ranges up to 4 miles, the nearest district has the right to the revenue. If the distance ranges between 4 – 12 miles, the provincial government receives the revenue, while if the distance exceeds 12 miles, the central government retains the revenue. The formula to calculate resource revenues is determined by the realization of production (*lifting*) of oil and gas.

Thus, oil and natural gas lifting determines how much revenue districts obtain every year from these resources. In contrast, for coal and other minerals, revenues are calculated based upon the total district area in which coal companies have a license to operate, as well as by production volumes and the sales price. These variables are used to formulate *Land rents* and *royalties* as a reference to calculate coal and mineral resource revenue. Whereas land rents are fixed, royalties are paid by the company per unit of production. They can be written as follows:

$$Land\ rents = Total\ Area\ \times Tariff$$

$$Royalties = Sales\ Volume\ \times Tariff\ \times\ Price$$

In summary, the allocation of resource revenues to districts follows strict percentage proportions managed by the Ministry of Finance based upon Law 33/2004. Under these rules, more resource productive districts receive a larger portion of revenues. Table 1 summarises the rules for the allocation of revenues from natural resources.

Table 1 Percentage of Point Source Natural Resources Revenue Sharing Allocation

No	Type of Natural Resources	The Law of 33/2004		
		Central Government (%)	Province Government (%)	District Government (%)
1	Oil	84.5	3.1	6.2
2	Natural gas	69.5	6.1	12.2
3	Coal and other minerals (Land rents)	20	16	64
4	Coal and other minerals (Royalties)	20	16	32

Source: DJPK Depkeu, Ministry of Finance, Republic of Indonesia (Type of natural resources is restricted only for "point-source" resources type)

Meanwhile, resource-poor or resource-absent districts still receive a windfall, but a much smaller portion. Note that, because of transfer rules between the central and provincial governments, those districts situated within the same province as resource-rich districts may receive higher transfers than similar districts in other provinces without such neighbours. At the extreme, if no resource-rich district exists within a province, a district within it will receive no windfall.

5 Data and Empirical Estimation Strategy

5.1 Scope of Analysis

Indonesia has been repeatedly included among samples of resource-rich economies in cross-country regression analysis. However, little comprehensive analysis has been conducted within the country. This is particularly true in the era following Indonesia's "decentralization" of powers to provincial and district levels. This study therefore limits its scope to within Indonesia analysis, following rural districts and urban municipalities over time in the period following decentralization. Using districts rather than provinces is relevant as Indonesian provinces do not have much administrative authority beyond their role in distributing resources upwards to the central government, or downwards to district.

Indonesia commenced its decentralization in 2001, and as of 2015 comprised more than 480 districts and municipalities. As explained in Section 3, each district obtains and manages revenues generated from resource extraction from the central government based on the proportions stated in Law No. 33/2004. As mentioned, these regulations generally tie distribution to the proportion of resources extracted from each district, so that revenues partially return to the districts where extraction took place. Since 2005, local citizens in each district have also started to elect their regional leaders, both for executive and legislative positions. As a result, districts are quite homogenous in terms of administrative and political processes, and in terms of regulatory background.

5.2 Data

Before describing the data and empirical estimation strategy applied in this study, it is necessary to distinguish two types of natural resource concepts used in this study: “resource *dependence*” and "resource *abundance*". I mainly focus on the effects of dependence for two reasons. First, abundance measures, such as estimations of oil and coal deposits, are not generally available at the district level, and certainly not over time as required for panel regression. Abundance measures are available at the provincial level, for some years, but this seems too coarse for within-country analysis for the number of years for which data is available. By contrast, measures of resource dependence based on economic output can be readily constructed at district level. Second, I focus on resource dependence because previous cross-country empirical studies have tended to use such measures, in particular the ratio of resource exports to total GNP or GDP. However, export data at the district level is not available, because records of export values are generally held on behalf of the port from which goods are sent overseas, and not the district of product origin.

Instead, I use a measure of *mining dependence* (which includes coal, oil, gas, and all minerals, including quarrying) similar to what has been employed by within-country papers such as Douglas and Walker (2016) or the closely relevant Indonesian study by Edwards (2016). Edwards employs mining and quarrying’s share of total GRDP for each district in

Indonesia using cross-sectional data, in 2009. I also use this measure for mining resource dependence in Indonesia, for the years 2005 to 2015.[26]

Some within-country studies have instead tried to capture resource dependence using resource revenues that flow to local governments as royalties, particularly in cases where central governments transfer large portions of revenues sourced from extraction activities back to producing regions. Since this is also the case for Indonesia, I employ additional measures of resource dependence, namely mining revenues (MINREV) defined as total revenues from oil (including natural gas) and coal mining that each district government receives, as a proportion of its revenues from all sources. I also decompose this alternative measure to separate the combined effect of oil and gas from coal revenue dependence, respectively. These data are obtained from several reliable publications by the the Ministry of Finance and the Audit Investigation Board (BPK) of the Republic of Indonesia from 2005 to 2015.[27]

Aside from resource revenue dependence measures, most of the data required for this study come from the "Indonesia Data for Policy and Economic Research" or INDODAPOER data base published by the World Bank.[28] INDODAPOER is a multipurpose dataset providing more than 300 indicators and currently covers the period from 1976 to 2013 at the district level.[29] INDODAPOER itself gathers information from official government sources, such as Susenas (the National Economic Survey, Republic of Indonesia), from the Indonesia Statistical National Agency (BPS), and from the Ministry of Finance. Unfortunately, most district level observations are missing for most variables prior to decentralization (1976-2003). Fewer district level observations are missing from 2003 to 2005, and virtually none thereafter. To populate missing observations from 2003 onward, I

---

[26] More specifically, 'mining' is defined as an economic activity to extract and prepare for further processing minerals in solid, liquid or gas form. Products include crude oil and natural gas, coal, iron sand, tin concentrate, nickel ore, bauxite, copper concentrate, gold, silver, and manganese. Quarrying, in contrast, is an economic activity that covers extraction of all quarried commodities. These include chemical elements, and mineral and rock sediment below the ground (excluding metal, coal, petroleum, natural gas and radioactive elements). Quarrying commodities include stone, limestone, marble, sand, quartz sand, kaolin, and clay. For a more detailed explanation, see: https://www.bps.go.id/Subjek/view/id/10#subjekViewTab1

[27] The BPK publications can be downloaded using this link: http://www.bpk.go.id/lkpp , while the data from the Ministry of Finance can be accessed by opening the link: http://www.djpk.depkeu.go.id/?page_id=307

[28] The datasets can be downloaded using: http://data.worldbank.org/data-catalog/indonesia-database-for-policy-and-economic-research.

[29] I define districts to include rural districts (*kabupaten*) and urban districts (*kota*/municipalities).

use the statistical yearbook published by the BPS.[30] The list of variables and their definitions is presented in Appendix 1.

Ultimately, I elected to restrict the years of analysis to between 2005 and 2015. I excluded 2003 and 2004 because prior to 2005 there is evidence of some unevenness in the quality of the district level data, due to the political transition to downward democratization under the decentralization framework established between 1999 and 2003.[31] There were also some revisions to the fiscal mechanism for revenue sharing for Law 22/1999 concerning regional governments and Law 25/1999 concerning revenue sharing made in 2004 under Law 33/2004. The modifications of this law were announced in 2004, and effectively implemented in 2005. Thus, only by 2005 were both elections and revenue sharing effectively implemented by all districts.[32]

When I try to follow Indonesia's districts over time, an obstacle arises due to a rapid increase in the number of districts after 2005 caused by a "proliferation" policy. As discussed in Section 3, Indonesia's central government decentralized their authority to provinces and districts. This was predicated on the view that it is good to make local government closer to the people in order to spur improvements in public service delivery. This policy resulted in the number of districts rising from around 370 in 2003 to more than 500 by 2015. To facilitate longitudinal analysis, I merge "children" districts back into their "parent districts" using the annual population of each child to create weighted averages. Since most districts existing in 2015 were identifiable from parent districts in 2003, I have chosen this year as a benchmark when aggregating districts back to their earlier forms.

More specifically, I begin with the number of districts in 2015 (including the older and the newer districts). From this complete list, I merge the new districts back to their parent districts down to the districts existing in the year 2003.[33] This results in 390 consolidated districts in 2015, down from 512. While this procedure loses observations for

---

[30] This can be freely downloaded from https://bps.go.id/index.php/Publikasi .

[31] Initially, the "big bang" reform of 1999, and approval of Indonesia regional autonomy began in 2001, followed by presidential approval of elections. However, there were challenges to implementation over the first five years as debate escalated over revenue sharing turns, and delays in the implementation of local political elections at the district level.

[32] The number of provinces and districts which perform local elections can be seen here: http://otda.kemendagri.go.id/CMS/Images/SubMenu/Rekap%20Pilkada%202005%20s.d%202014.pdf.

[33] The 2003 list of districts comes from the Ministry of Home Affairs. I excluded the regions of Jakarta (Central Jakarta, West Jakarta, East Jakarta, South Jakarta, Kepulauan Seribu) and Tanjung Pinang district. Jakarta is excluded because it is not defined as a district under decentralization law. The final district is omitted because of lack of data availability over time.

later years, it ensures that no district values are missing during the period 2005-2015, creating a balanced panel.

5.3 Estimation Strategy

I use three regression forms to estimate the effects of resource dependence on output: a panel fixed-effect regression following districts in Indonesia, a first-difference regression, and a first difference regression with instruments to mitigate the potential endogeneity of my resource dependence measures.

5.3.1 Model 1: Fixed Effects Estimator

By effectively including a dummy variable for each district, fixed effects models consider the influence of stable but unobserved district characteristics that could be influencing output, quite apart from resource dependence (Wooldridge 2016). With 390 districts followed over 11 years, my data are relatively large in cross section dimension, N, but small in time-series dimension, T, or a "shallow" panel.

The Fixed Effects (henceforth FE) approach is driven by two concerns: to control for the variations *across* districts (i.e. the average of variables between districts) and to control for variation *within* districts over time (Wooldridge, 2016). More formally, if the panel regression model is written as: $Y_{it} = \alpha_i + X_{i,t}\,\beta + \varepsilon_{i,t}$, the time-average of each variable can then be written as: $\overline{Y_i} = \alpha_i + \bar{X}_i\beta$. If we substract the latter equation in means from the former equation, we get: $Y_{i,t} - \overline{Y_i} = \left(X_{i,t} - \overline{X_i}\right)\beta + \varepsilon_{i,t}$. As this difference illustrates, fixed effects eliminates the district specific effects α_i caused by unobserved heterogeneity between districts.

For FE estimation, I use the following model:

$$Ln(GRDP)_{i,t} = \alpha_{i,t} + RD_{i,t}\beta + X_{i,t}\,\beta + \mu_i + \delta_t + \varepsilon_{it} \qquad (1)$$

Here GRDP is per capita Gross Regional Domestic Product (real prices in 2000) of district i at time t, where i =(1, ..., 390), and time t = (2005,….,2015). The natural log of GRDP is used following standard growth models, and is useful for mitigating problems such as potential skewness or stationarity that often occurs in annual income panel data that increases over time (Wooldridge, 2016). For example, the log of real GRDP is used in resource curse studies by Mamun, et al. (2017), Bjorvatn, et al. (2012), Sarmidi, et al.

(2014), and Cust and Rusli (2014, 2016). A final benefit of using logs is that the resulting coefficients on control variables can be easily interpreted as elasticities (if in double-log form). Note that my dependent variable is in levels, which differs from Sachs and Warner, who used average or change in GDP, because I perform panel rather than cross section analysis. Note that FE may solve the problem of unobserved district characteristics that affect output, but that it alone does not address potential endogeneity of resource dependence measures. I address this issue subsequently. [34]

To address unobserved heterogeneity, I include $N-1$ district fixed effects represented in (1) by μ_i. I also apply year dummies, δ_t, to control for any shock events common to all districts at a point in time, such as changes in commodity prices, business cycle fluctuations, or economic crises. The error term, ε_{it} is assumed to be independently and identically distributed (i.i.d).

My key independent variable in (1) is $RD_{i,t}$, the measure of natural resource dependence. As discussed in Section 4.2., I try several alternative proxies for this dependence. First, I use the share of overall real mining output in total district real GRDP (MINDEP). A similar measure has been used by Papyrakis and Gerlagh (2007) in the case of the United States, and by Edwards (2016a,b) in the case of Indonesia. Second, I use the share of the district government's revenues that come from overall mining, or oil and gas alone, or coal alone. This approach follows recent sub-national investigations of the effects of resource windfalls associated with resource extraction. For example, resource revenues are transferred on the basis of "producer origin" under decentralization in Brazil. I thus follow an approach inspired by Casselli and Michaels (2013), Bjorvatn, et al. (2012), Cust and Rusli (2014, 2016) and Douglas and Walker (2016).[35] These measures are respectively labelled as share of combined oil, gas and coal mining revenues over total district budget revenues (including from offshore and onshore operations) (MINREV), the share of oil and gas revenues over total revenues (OILGASREV), and the share of coal revenues over all revenues (COALREV).

[34] Lederman and Maloney (2006) update Sachs and Warner's seminal work by applying panel data fixed effects. This approach is also followed by Manzana and Rigobon (2001).

[35] Komarulzaman & Alisjahbana (2006) and Loayza & Rigolini (2016) also use a similar measure of resource dependence. Cust & Poelhekke (2015a) discuss the importance of observing the effects of revenue based on natural resources under fiscally decentralized systems.

Finally in (1), $X_{i,t}$ is a matrix comprising other determinants of GRDP per capita, such as the total number of annual earthquake events at the district level, the labor force participation rate, and the proportion of households with access to electricity. The latter two variables range from 0-1. Some standard growth variables from cross-country studies, such as openness to trade (export activities) are unfortunately not available within country. Similarly, a variable proxying for private investment is not available at the district level. Positively, government capital expenditures at the district level are available, but will be used in subsequent analysis exploring the the causal channels of resource effects.

Edwards (2016) argues that mining value-added (i.e. the share of GRDP approach) can be the best practical measure of resource dependence because it captures direct impact. However government revenues from natural resources are also relevant since many rich resource economies re-distribute resource revenues across their counties. It is widely thought that the extent to which countries avoid the resource curse is related to how well they manage revenues generated from resource extraction, and invest it for the benefit of the wider population.

5.3.2 Model 2: First-Difference Equation

My second model is commonly used in growth research because it allows explanatory variables to have long term effects on either GDP or change in GDP as explained in Barro (1991). Similar to FE for 2 periods, first-difference or FD models control for unobserved heterogeneity in districts that affects growth (Wooldridge, 2016). Here I take a 10 year difference, $t_{2015} - t_{2006}$. I retain my earliest available year of 2005 as a baseline year to control for differing initial conditions between districts that can affect their subsequent growth. Controlling for initial GRDP is suggested and commonly implemented in previous resource curse studies (Sachs and Warner, 1995; Douglas and Walker, 2016; Edwards, 2016).

To see the equivalence between two period fixed effects and first difference models, I can follow Wooldridge (2016) and take the difference of panel data across two years, t and $t-1$. Specifically, the first-difference regression of panel data can be derived as follows:

$$Y_{i,t} = \alpha_i + X_{i,t}\beta + \varepsilon_{i,t} \tag{2}$$

$$Y_{i,t-1} = \alpha_i + X_{i,t-1}\beta + \varepsilon_{i,t-1} \tag{3}$$

Subtracting (3) from (2), we get the first difference form:

$$Y_{i,t} - Y_{i,t-1} = (X_{i,t} - X_{i,t-1})\beta + \varepsilon_{i,t} - \varepsilon_{i,t-1} \quad (4)$$

We can also write this as:

$$\Delta Y_{i,t} = \Delta X_{i,t}\,\beta + \Delta\varepsilon_{it} \quad (5)$$

Wooldridge cautions that first-difference models can result in large standard errors when estimated using OLS. It is important therefore to use a large cross section, or sufficiently long differences in time (Wooldridge, 2016). Here, I use the longest possible change of 9 years for my first-difference model. However, the downside of this strategy is that it reduces the sample size to effectively that of a single year cross-section model. Notwithstanding this limitation, the first difference model has the advantage of being widely used in the resource curse literature, and of being a good "bridging" model for attempts to deal with potential endogeneity of resource dependence measures using cross sectional instruments.

Applied here my first difference model is:

$$\Delta Ln(GRDP_i) = \Delta RD_i\beta + \Delta X'_i\,\sigma + \Delta\varepsilon_{it} \quad (6)$$

Here $\Delta Ln(GRDP_i) = ln(GRDP_{i,2015}) - ln(GRDP_{i,2006})$, and it measures longer term changes in the log of GRDP. The change in GRDP measure follows the growth measure used by Douglas & Walker (2016), Walker (2013), Papyrakis and Gerlagh (2004, 2007), James and James (2011), and James and Aadland (2011) in within-country studies for the United States.[36] The explanatory variable, ΔRD_i, is the change in the level of resource dependence in district *i*. The $\Delta X'_i$ stands for a set of control variables including changes in labor force participation rate, initial level of population in 2005 (in logs) and the total number of earthquake event over the last 10 years. Initial population is included as a control to test for potential pro-growth effects of economies of scale. Some additional level dummies are included to capture whether districts are urban (a municipality) (DURBAN),

[36] Douglas and Walker (2016) and Walker (2013) measure the difference in log per capita income over 10 year periods as: $GRDP_{i,t} = \left(\frac{1}{10}\right)(LnGRDP_{i,t,2015} - LnGRDP_{i,t,2005})$. Other authors mentioned above using the formula as: $G^i = \left(\frac{1}{T}\right)\ln(Y_T^i / Y_0^i)$.

and located on Java Island (DJAVA). By including these controls, which would have washed out of annual FE, I can control for the differences between regions of Indonesia. Historically, Indonesian investment and infrastructure development has not been broad based, but more concentrated in Java.

As commonly used in growth models and resource curse studies, I also control for the log of initial GRDP per capita in 2005. In a first difference setting, this variable tests for convergence in GRDP between districts as suggested in traditional growth theory (Barro (1991) and Temple (1999)). A negative coefficient on baseline GRDP would be interpreted as evidence that poorer districts have subsequently had higher growth rates between 2006-2015, catching up to richer districts.

5.3.3 Model 3: First-Difference with Instrumental Variables (IV)

Several key resource curse papers criticize the commonly used measures of resource dependence as being very likely to suffer from endogeneity. As it is commonly measured as a ratio, where the denominator captures all economic activities (GDP or GNP) similar to the dependent variable, this measure may not be sufficiently independent, and thus can not be assumed exogenous. One way to address potential endogeneity is to find valid instruments for resource dependence. In my first difference model, I treat the ΔRD_i variable as potentially endogenous, and seek a suitable instrument for it. I do not use an instrument in my annual panel model because my main instrument is time invariant.[37]

Theoretically, a valid instrument must be correlated with the potentially endogenous regressor in the first-stage regression, and must not be correlated with the error term. In sourcing potential instruments, I follow the strategies of Edwards (2016) in an international cross-country context, Caselli and Michaels (2013) in the case of Brazil, and Cust and Rusli (2016) in Indonesia. These authors all use an instrument of past resource abundance, and this strategy fits well with the nature of the resource dependence measure that I use in this analysis.

[37] I do not pursue using the lag of the dependent variable in annual panel models (known as a dynamic panel model using System GMM). I do not use this method because it may introduce a bias, which could lead to wrong inference under the null hypothesis significance test (Bellemare, Masaki, and Pepinsky 2015).

In particular, Edwards has instrumented the ratio of mining to total GDP in 2005 with international estimated fuel reserves in 1971 when using his international dataset.[38] Similarly, Caselli and Michaels instrument for government oil revenues (at municipality level) using past oil output in Brazil, while Cust and Rusli use past offshore oil and gas production in Indonesia. All of these approaches seem likely to generate instruments that are correlated with subsequent resource dependence, because abundance is a logical pre-condition needed for production and dependence on resources. Cust and Rusli specifically use a change form for their instruments (the change in physical offshore oil and gas production between 1999 and 2009) for Indonesia. However, their concern is with the effects of oil and gas, not coal mining. It is important to capture coal mining because this resource in particular experienced a boom in Indonesia in the early 2000's.

Following Edwards, Caselli and Michael, and Cust and Rusli, in my third model, I instrument for ΔRD_i using each district's historical level of resource abundance, RA_{1970s} . I try both continous and binary versions of abundance levels based on merging historical maps of natural resources in Indonesia with district level maps as of 2003. For the binary instrument versions, I classify districts as "oil/gas abundant" if they had at least one proven major field as of the 1970's, and as "coal abundant" if at least 20 percent of the district was covered by "first contract" agreements with coal companies as of the 1980's. For the continous instrument versions, for oil and gas I use the number of major or minor oil and gas fields in the 1970's.[39] For coal I divide coal deposit areas by total district areas according to first generation coal agreement contracts in the 1980's as shown in an original map by Leeuwen (1994) and Frederich and Leeuwen (2017). See Table 2 for a summary of these instruments.

My historical abundance level instruments are produced using original historical maps released by Bee (1982) and Leeuwen (1994, 2017). ArcGIS software was used to match geographic coordinates of oil/gas fields or coal exploration agreement areas according to the Bee, Leeuwen, and Frederich and Leeuwen maps with specific district boundaries as of 2003. This matching procedure resulted in new maps, illustrated in Appendices 2-5. These new maps enable me to exploit historical information regarding oil,

---

[38] Edwards also regresses mining contribution on various development indicators at district level in Indonesia in 2009. However Edwards does not apply instrumental variables.

[39] For coastal oil fields in particular, I only consider onshore and offshore oil and gas wells, within 4 miles from the coastline of the related districts as laid out under Law 33/2004 of the Republic of Indonesia.

natural gas, and coal mining abundance as of the 1970's (for oil and gas) or the 1980's (for coal). By this time, knowledge of resource locations had accumulated based in part on exploration efforts by the Dutch when Indonesia was a colony. Yet this period also immediately preceeded a "golden era" of natural resource commercialization in Indonesia.

While abundance is a logical pre-condition for dependence, the *ex ante* grounds for expecting correlation between *change* and levels of abundance seems weaker. Nonetheless, I also try to construct a change form of an instrument. This is difficult to do since it requires a reliable measure of resource endowment, deposit or reserve at district level over the two years of 2015 and 2006. Since such data is not publicly available from the Indonesian government, I follow the approach of Caselli and Michaels (2013) and of Cust and Rusli (2016) in using an instrument based on changes in levels of physical oil and gas output. Note that physical resource output functions less as a logical pre-requisite for resource dependence, than a simultaneous correlate of resource dependence. Data on oil and gas lifting are released by the Ministry of Energy and Mineral Resources (MEMR).[40] These data are used as a basis for district revenue redistribution calculations. With regard to coal dependence, I use instead Rupiah measures of land rents summed with royalties as an instrument.[41] With these change instruments, ΔOil_i and $\Delta Coal_i$ constructed over 9 year differences (2015 minus 2006), the first stage regression can be written as follows:

Returning to my third model, the first difference specification can initially be expressed as follows:

$$\Delta LnGRDP_i = \beta_0 + \beta_1 \Delta RD_i + \Delta X'_i \, \beta_2 + \Delta\varepsilon_{it} \qquad (7)$$

With instruments constructed, the first and second stage regressions are modelled as follows:

$$\Delta RD_i = \alpha_0 + \gamma RA_{1970s} + \gamma \Delta OIL_i + \gamma \Delta GAS_i + \gamma \Delta COAL_i + \Delta X'_i \, \beta_2 + \Delta\varepsilon_{it} \qquad (8)$$

$$\Delta LnGRDP_i = \pi_0 + \pi_1 \Delta \widehat{RD}_i + \Delta X'_i \, \pi_2 + \Delta\varepsilon_{it} \qquad (9)$$

[40] In practice, oil and gas lifting data is used under the decentralization scheme (Law 33/2004), to calculate resource revenue sharing across districts. The same rule also applies for coal, using land rent and royalties as a basis for coal revenue allocation.

[41] The land rents and royalties rely heavily on coal production. Indonesia formulates land rents as a fixed tariff that must be paid by coal producers based on their licenses, whereas they pay royalties per unit of output.

Thus I treat the change in resource dependence, ΔRD_i, as potentially endogenous and use level measures of resource abundance, RA_{1970s}, and changes in physical resource output, as instruments. When total resource dependence is considered, using either MINDEP or MINREV, I use all instruments together, both in level and in change forms. When resource dependence is measured as oil and natural gas separately from coal, however, I use only a single abundance instrument associated with the particular type of dependence. Why might such positive correlation occur? In the case of oil and gas, the considerable capital and risk bearing needed to ramp up extraction following succesful exploration could lead to a positive correlation. In the case of coal, first contracts only reveal the potential for viable coal deposits to be found, which would require time to confirm with geological sampling.[42]

Table 2 summarises my various instruments, and how they relate to my various measures of resource dependence.

Table 2 Instrument Summary

	Resource Dependence Measure	**Instruments – Level**		**Instruments – Change**
		Binary	**Continous**	
ΔRD_i	$\Delta\left(\frac{GRDP_{mining}}{GRDP}\right)$	- Oil + Natural Gas Abundance 1970's - Coal Abundance 1980's	- Oil + Natural Gas Abundance 1970's - Coal Abundance 1980's	- Change in oil production - Change in gas production - Change in coal production
	$\Delta\left(\frac{Revenue_{mining}}{Total\ Revenues}\right)$	- Oil + Natural Gas Abundance 1970's - Coal Abundance 1980's	- Oil + Natural Gas Abundance 1970's - Coal Abundance 1980's	- Change in oil production - Change in gas production - Change in coal production
	$\Delta\left(\frac{Revenue_{oil+gas}}{Total\ Revenues}\right)$	- Oil + Natural Gas Abundance 1970's	- Oil + Natural Gas Abundance 1970's	- Change in oil production - Change in gas production

[42] By looking at the current main locations map of natural resources extraction activities provided by the Ministry of Energy and Mineral Resources, no dramatic shift occured over the 2006-2015 period. Thus, there is no way for district governments to experience resource windfalls in 2015 without having successfully proven deposits, 30-40 years before.

	Resource Dependence Measure	Instruments – Level		Instruments – Change
		Binary	Continous	
	$\Delta\left(\frac{Revenue_{coal}}{Total\ Revenues}\right)$	- Coal Abundance 1980's	- Coal Abundance 1980's	- Change in coal production

For all instrumental variables estimation, I use two step feasible efficient Generalized Method of Moments (GMM2S) with robust standard errors rather than two stage least squares (2SLS) to address the potential presence of heteroskedasticity and produce more efficient estimates.[43] I then perform validity tests of whether my instruments are sufficiently relevant and sufficiently uncorrelated with the error term (instrument "exogeneity"). Relevance can be checked using the F statistic of first stage regressions, or using the Cragg-Donald Wald (if error terms are assumed to be identically and independently distributed) or Kleibergen Paap rk Wald test values against Stock-Yogo critical values (Schaffer, Baum, and Stillman 2003; Baum, Schaffer, and Stillman 2007). Instrument exogeneity can be checked with overidentification tests such as Hansen's J-Statistic.[44] Overidentifications tests require the number of instruments to exceed the number of suspected endogenous regressors.

6 Empirical Results

Summary statistics for annual panel and first-difference data are shown in Tables 3 and 4, respectively. My dataset uses 4,290 observations for 390 districts for annual panel specifications and 390 district changes in first-difference models. In annual FE, the average real GRDP per capita (in logs) is 4.13 and the standard deviation is 0.690. The mean share of mining GRDP in total GRDP is about 9.0 percent, while the share of mining revenue over all district government revenues is about 5.3 percent.

[Tables 3 and 4 about here]

Figure 6 presents a scatterplot of the correlation between real GRDP per capita and mining dependence (MINDEP) as measured by the share of mining over total GRDP. Both variables are an average value for the 11 observations between 2005 and 2015 for each

[43] I use the ***ivreg2*** command in the STATA module developed by Baum, Schaffer, and Stillman (2007).
[44] The ***ivreg2*** command provides diagnostics to check for instrument relevance and exogeneity.

district. As shown, overall, as MINDEP increases, economic performance rises, which implies a positive relationship between income per person and district economic reliance on mining. I also add a linear trendline generated from Excel which shows a positive relationship. Recall here that mining is defined as a broad measure, as a summation of oil/gas and coal revenues.

Figure 6. Mining Dependence and Real GRDP per capita (averaged over time for each district)

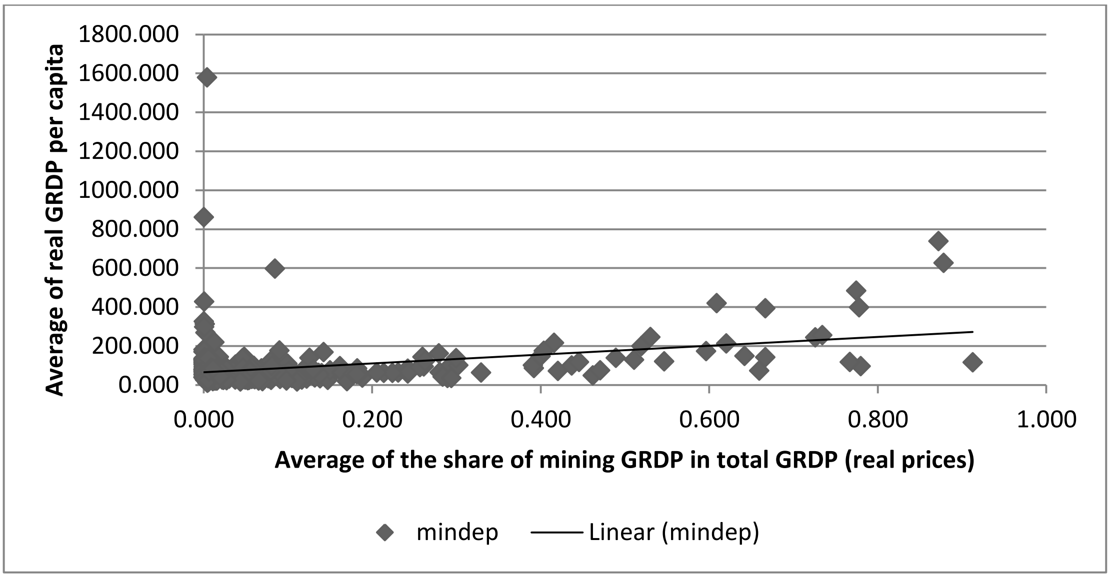
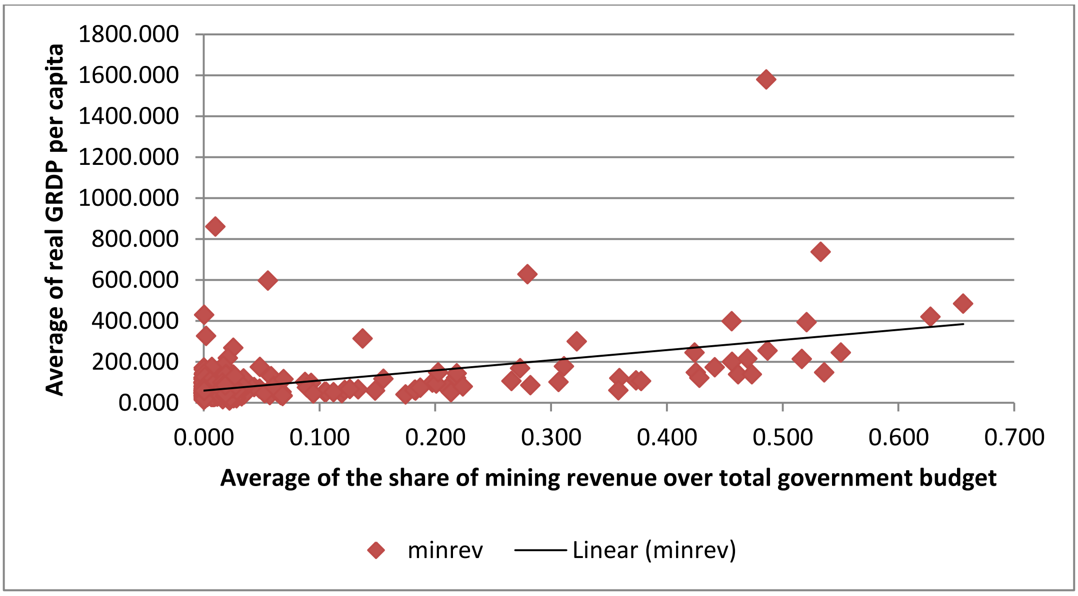


Figure 7. Mining Revenues and Real GRDP per capita (averaged over time for each district)



Next, Figure 7 above shows a similar pattern for my second type of resource dependence measure—district government revenues from mining over all sources of revenue. Once again, each observation represents an eleven year average for each district. Here again, a simple regression line through the scatterplot has a positive slope, contrary to a resource curse prediction. To test for resource effects more formally, I now move to regression results.

6.1 Annual Panel Data Results

As a baseline, I describe results in Table 5 from annual FE regressions at the district level, using the period 2005-2015 (Table 5).[45] Real GRDP per capita (in logs) is used here as the dependent variable. The impact of all four resource dependence measures is presented in models (1) to (4). Similar to the scatterplots, the first model shows a surprising sign according to the standard resource curse hypothesis. I find that mining dependence (shown in model (1)) is positively associated with real GRDP per capita at the local level in fixed effects analysis. That is, districts that increase in dependence (measured through mining's share of district GRDP) have larger per capita GRDP, on average. The coefficient on MINDEP in model (1) seems especially strong. Here, a one standard deviation increase in MINDEP (0.179) is associated with an increase in real district income per capita of (0.179*0.406 = 0.0727) 7.27 percent, on average, all else equal.

Coal resource revenue dependence looks to have a negative effect on GRDP per capita. In contrast, oil and gas dependence has a positive sign but insignificant effect. Thus, combined oil, gas and coal dependence has a coefficient near zero and not statistically significant. At first glance, these results may indicate that resource dependence in overall output is good for GRDP, while dependence in government budgets has either no effect, or possibly a negative effect on GRDP for coal in particular. That is, the resource that comes closest to resource curse predictions is district government coal revenue dependence.

Looking at other control variables in Table 5, the frequency of earthquake events appears to be negatively associated with GRDP over time, though only at the 10 percent level. As the earthquake variable is defined as the annual number that each district experienced between 2005-2015, model (2) finds, for example, that one additional

[45] Because in subsequent first difference analysis I compare 2006 to 2015 results, I have also run the annual fixed effects analysis using 2006 to 2015 data only. The results are virtually identical. Results are available from the author upon request.

earthquake decreases real per capita GRDP by 0.0168 percent. This seems reasonable as the damage from earthquake occurrence reduces economic performance and raises risks of investment in new goods and services, which can lower growth. Other controls, such as the labor force participation rate has a positive coefficient but is insignificant. Surprisingly, the proportion of households with access to electricity is not significantly associated with local GRDP per capita.

[Table 5 is about here]

Overall, my FE results do not seem to support the standard resource curse hypothesis, with a possible exception for local government dependence on coal mining revenues. They do not support the view that non-renewable resources lead to reduced local GDP. These results are similar to those found by Cust and Rusli (2016) at the district level in Indonesia and in line with some blessing effects found by other researchers as summarized in Appendix 5. However, in spite of controlling district fixed effects and year effects, the potential endogeneity of my four resource dependence measures has not been addressed, and I do not have suitable annual instruments to do so. Thus, my first assessment using FE models is inconclusive. Therefore I move next to a first-difference model, using 2015 and 2006 as the final and initial years, respectively.

6.2 First-Difference Estimates

In the first-difference model (FD hereafter), I include some level dummy variables to capture the urban/rural nature of districts (DURBAN) and potential spatial benefits of being a district in the centrally located island of Java (DJAVA). Note that such unchanging characteristics could not be retained in fixed effects analysis. With a direct measure of urban/rural status, I no longer use household access to electricity, but I still use the sum of earthquakes at level. As mentioned previously, I now also include initial real GRDP per capita in 2005 (in logs) to control for initial economic conditions, and to test for a convergence in per capita GRDP between initially richer and poorer districts. Additionally, I also control the size of initial district population in 2005 to test for gains to growth from economies of scale.

Table 6 reports the effect of changes in mining dependence on changes in longer term in real GRDP per capita again using four different measures of resource dependence. As with FE, I find a positive association between rising output dependence and higher growth.

In model (1), a standard deviation increase in mining's share in local GRDP is associated with a (=0.142 * 0.738 = 0.105) 10.5 percent higher long run growth rate in GRDP per capita. As with FE, the effects of government dependence on resource revenues is less conclusive. In model (2), the coefficient on oil and gas revenue dependence is negative, but not statistically significant, similar with coal effect in model (3) even though the sign is positive. Therefore, when I aggregate both oil and gas and coal, neither are statistically significant (see model (4)). With potential endogeneity of my resource dependence measures not yet addressed, I find evidence that overall resource output dependence is positively associated with growth in real GRDP, and no clear association between government revenue dependence and growth in GRDP.

[Table 6 is about here]

The impact of earthquake frequency on district economic performance is also similar to that found in FE in all models. Note that for FD models the earthquake variable is defined as a cumulative total of each district's earthquakes over the 10 years (2006-2015). What is new in Table 6 is the strong effect on subsequent growth of initial real GRDP per capita (in 2005). The coefficient on baseline GRDP per capita is negative in all four models at the 1 per cent level. My finding here is consistent with convergence of incomes between poorer and richer districts during the decentralization period.

Among other control variables, the sign of the dummy variable, DURBAN, is positive, though not statistically significant in any specifications. Similar results occur for DJAVA, though with slightly stronger evidence that districts in the historically more developed island of Java look to have grown more rapidly since decentralization than other districts. In model (1), in particular, Java's districts (excluding the capital Jakarta) grew 8.81 percent higher between 2006 to 2015 than non-Java districts though the effect is significant only at the 10 % level. [46]

The FD results seem broadly similar to those from FE models with resource dependence in GRDP a blessing, and dependence in government budgets neutral. Nonetheless, the resource dependence findings in these models are not addressing the possible endogeneity of my resource dependence measures. I thus move to results using FD estimation with instrumental variables.

[46] To interpret dummy explanatory variables when the Y variable is in logs form, I follow the formula 100.[exp($\widehat{\beta_i}$) $- 1$] (see Wooldridge, 2015, p.212).

6.3 First-Difference Estimates With Instrumental Variables

For my final results, I add two types of instrumental variable (IV) analysis to a FD model. Recall the first type are historical abundance instruments in levels, using either continous or binary forms. The second are changes in physical output of oil, natural gas, and coal production.

Table 7 provides results using the continous form of abundance-based instruments along with the physical output instruments. Recall that the instruments are defined as the total number of major and minor petroleum (oil and natural gas) fields, in the 1970's, and the relative share of coal deposit areas to total district areas, in the 1980's. For comparison purposes, I place the earlier OLS results side by side with IV-GMM results.

I start with whether the instruments satisfy the relevance and overidentification tests. In general, the instruments are fairly strong, particularly for oil/gas and coal resource dependence for models (3′)-(4′). As shown, the Kleibergen Paap Wald F statistic ranges from 16.834 in model (1'), to 25.347 in model (4), exceeding Stock and Yogo critical values at the 10% maximal IV size (the critical value is 19.93), with the exception of model (1), where it exceeds the 15% maximal size. Alternatively, as shown in Table 7, according to Cragg-Donald F statistic values, we see relevance increasing from models model (1′) to (4′). However, I emphasize Kleibergen F statistics that are robust in the presence of heteroskedasticity. Likewise, regarding overidentification, the Hansen J statistic fails to reject the null hypothesis of exogenous instruments in any models from (1') to (4'), though with the lowest p value in model (2') of 0.1486. This confirms that my instruments are valid.

[Table 7 is about here]

With the performance of my combined instruments appearing fairly strong for all models, I next test whether the change in resource dependence, ΔNR_i, is endogenous. In model (1'), the p value from a Hausman type endogeneity tests cannot reject the null that mining dependence (model (1′)) is exogenous (p value 0.2481). However, endogeneity tests reject exogeneity in IV-GMM models (3') to (4') at the 5% level, with P values of 0.0149 and 0.0178, respectively. In model (2') the p value is close to borderline, at just above the 10 percent level (0.108). Therefore, with exogeneity rejected or borderline rejected for 3 of 4 models, I move next to describe second stage IV results.

Just as in the FD case without instruments, I find no evidence that higher non-renewable resource dependence creates an adverse effect on growth. As clear from models (1′), (2′) and (3′), on the dependence change measures increase in their magnitudes with use of instruments, and are significant at the 1 percent or 5 percent levels. Under the IV-GMM estimator, a change in district government dependence on oil and gas revenues in model (3′) has the largest estimated coefficient. Here, an increase of a standard deviation in oil and gas revenue dependence, on average, increases long run growth in real income per capita by (0.091*1.765 = 0.1606) 16 percent. For its part an increase in coal revenue dependence continues to have no significant effect on long run growth as instruments are included, though the sign of the coefficient turns negative. This finding once again does not confirm Sachs and Warner's negative findings in a within-country case. Instead, these results support the views of many earlier descriptive papers for Indonesia considering the effect of the oil boom of the 1970's and 1980's (see Gylfason, 2001; Rosser, 2007; Sovacool, 2010).

The effects of other control variables are generally similar to the FD model without instruments. For example, the cumulative number of earthquakes over 10 years negatively affects per capita income growth at district level in Indonesia in all four models of resource dependence. Initial GRDP per capita again has a strong negative association with district income per capita, indicating convergence as before.

Given no evidence of a resource curse with continous abundance level instruments (combined with change in physical production instruments), I next estimate the same models but now using binary abundance level measures, combined with change in physical production measures. As previously described, a binary variable for oil/gas abundance takes on a value of 1 if a district has a major oil field and 0 otherwise; that for coal abundance takes a value of 1 if the district has a proportion of 20 percent or more with coal deposits, and 0 otherwise. Results are provided in Table 8. Kleibergen F statistics indicate that the binary abundance instruments generally are strong for models (2′), (3′) and (4′), with F values of 13.896, 30.976 and 27.580, respectively. More importantly, overidentification test p values are now everywhere for above rejection thresholds in all models. Thus the binary abundance instruments combined with physical production change instruments are valid, albeit still with some weakness in model (1′).

Moving to findings, Table 8 shows that results are similar when the binary abundance instruments are used in place of continous ones. The coefficients on resource dependence are positive, and significant for oil/gas and for oil/gas and coal combined. Taking oil and gas revenue dependence as a firm example in model (3′), a one standard deviation increase in the share of oil and gas revenue over total government revenues is associated with an increase in long run per capita GRDP growth of about (0.091*1.359 = 0.1236) 12.36 percent. Once again, with binary instruments as without instruments, there is no significant association between rising coal revenue dependence and growth.

In the analagous endogeneity tests using binary abundance instruments, I again find that exogeneity cannot be rejected in model (1′), and can be rejected in model (3′). In contrast, evidence of endogeneity is now stronger in model (2′) rather than borderline (p value 0.063), and weaker in model (4′) (p value 0.167).

[Table 8 is about here]

Regarding other control variables with binary abundance instruments, earthquake frequency still has negative and statitsically significant effects, as I found in the previous results. The coefficient on initial district population level is not significant across models, suggesting no benefits of economies of scale on growth. The initial GRDP per capita in 2005 is statistically significant at the 1 percent level across all specifications, again implying that a convergence is occuring in real income levels between districts during the 2006-2015 period.

7 Discussion

My estimation results seem consistently contrary to the predictions and some findings of the resource curse literature. I find a positive or no significant association between various measures of resource dependence and levels or growth in GRDP, using fixed effects models and first difference models, with and without instruments. This lack of negative association persists when I control for relevant growth variables, and control for district and year fixed effects as well as initial income levels (real GRDP per capita) and control for population, labor force participation, and urban/rural status. There is instead some evidence that resource dependence seems to confer a blessing effect, particularly when measured using overall mining's share in GRDP, or in overall or oil/gas revenue dependence. For its part, coal revenue dependence seems to confer a neutral effect, neither a significant blessing nor a curse, lacking statistical significance in almost all specifications.

Table 9 Summary of Results

	(1)	**(2)**	**(3)**	**(4)**
FE	+	■	■	−
FD	+	■	■	■
FD with instrument 1	+	+	+	■
FD with instrument 2	+	+	+	■

Notes: FE = Fixed Effect; FD = First Difference; Instrument 1 is continous+changes of physical production; Instrument 2 is binary+changes of physical production;

Why might resource dependence in output, or in oil and gas revenue dependence, confer benefits for GRDP within Indonesia, when it does not seem to have elsewhere? There are several factors which could contribute: (i) the commodity boom prior to the data of this study, (ii) the effects of Indonesia’s decentralization policy, (i.e. improvements in institutional quality triggered by decentralization); (iii) the effects of quality of public spending on investments, such as education or infrastructure.

First, the oil boom during the 1970’s and 1980’s, and the coal boom during the 2000’s, have tremendously contributed to Indonesia’s non-tax revenues, which even before decentralization of resource revenues has made growth more progressive in the outlying regions of Indonesia. Resource-rich regions, mostly situated in Kalimantan and Sumatra, have enjoyed high incomes because of their historical abundance of natural resources. Far from this income being a “curse”, regional dynamic studies of Indonesia have identified most resource-rich regions in Eastern and Southearn Kalimantan and Sumatra Island as consistently being the most prosperous regions according to GRDP per capita between 1999 and 2011 (Hill, Resosudarmo, Vidyattama, 2008; Hill and Vidyattama, 2013; 2016). My results support this evidence, and similarly confirm Cust and Rusli’s (2016) study that finds that government revenues driven by oil and gas royalties have significantly increased district GRDP.

In particular, as indicated earlier by national level studies of Indonesia such as Usui (1997), Rosser (2007), di John (2011) and Chandra (2012), my results are in line with earlier work showing that Indonesia has avoided a resource curse. These studies argue that Indonesia successfully escaped a Dutch disease or resource curse more broadly during 1973-1985 as a result of managing its oil windfalls to strengthen both its agricultural and manufacturing sectors. Although such “activist” industrial policy interventions have not persisted, they may have benefited resource intensive regions in the years prior to decentralization.

Second, Indonesia is an archipelago country consisting of five large islands and more than 450 districts. With the implementation of decentralization, there is scope for considerable variation in regional government policies. Spillover effects from more successful districts, or competition between local leaders, has been implicitly encouraged by the central government through a system of rewards and punishments.[47] To the extent better governance can forestall a resource curse, Indonesia's decentralization may have contributed by creating incentives for better local governance.

To provide an example, take the fiscal rules implemented since 2005. The mechanism designed to redistribute windfalls across districts may have contributed to expanding the ability of poorer local governments to finance themselves. This could raise local living standards as predicted by Aragon, Chuhan-Pole, and Land (2015), if the revenue streams derived from oil are used to fund local public provision of infrastructure and education. Therefore, if it is true that a key factor to escaping the resource curse is how well a country manages its resource revenues, the incentives of decentralization for good governance at the local level may explain Indonesia's positive resource outcomes.[48]

In support of this "good governance" explanation, Bostwana is often cited as an example of a country that established an effective system for prudential fiscal policy to manage mining revenues. It is then taken as an example among developing resource-rich countries of a society that has avoided a resource curse (Iimi, 2007). In Indonesia's case, where state corruption has historically been a problem, the central government undertakes some efforts to monitor what local governments do. Financial audit investigations, for example, have been conducted annually by the Indonesia Audit Board (BPK) since 2005. The BPK investigates the performance of the central government, including State Owned Enterprises (BUMN), but it also investigates local district local governments on some aspects of quality of their financial reporting. It thus creates accountability incentives even

---

[47] Theoretically, fiscal decentralization is believed to affect economic growth positively. Fiscal decentralization may aid growth under the assumption that this system leads to higher economic efficiency because district governments are better placed to provide local public services than central/national government. Furthermore, competition among district governments and the rapid mobility of local citizens may better match the preferences between governments and their local people (Davoodi and Zou 1998).

[48] For an example of this argument, see *Natural Resource Charter* (Second Edition), (www.resourcegovernance.org and www.naturalresourcecharter.org.)

at the local government level. The BPK announces their findings every six months, which has likely contributed to good governance. Similarly, since 2010, the Indonesian Ministry of Home Affairs has annually evaluated all district governments and ranked them based upon their overall performance index.[49]

The period of my analysis, 2005-2015, captures a time when substantive political participation was distributed to districts. It seems likely that this created improvements in public service delivery and accountability through the use of direct local elections. Of course, decentralization that increases the authority of local goverments could conceivably multiply the incidence of lower-level money politics, corruption, and inefficient allocation of public service delivery. However, local elections and heightened political participation can be a tool to make local citizens more aware of what their government does, which could in turn make resource revenue use more transparent. For example, district governments would find the resource revenues helpful for reaching the goals set for them in the Medium Term Regional Development Plan (*Rencana Pembangunan Jangka Menengah Daerah*(RPJMD)). All levels of government are obliged to show how they fulfill this plan. The contents of these plans are themselves based on campaign promises of the winning parties during election campaigns.

Other researchers also, such as Cust and Poelhekke (2015) and Aragon, Chuhan-Pole, and Land (2015) in their survey paper, emphasize that government spending effects may be responsible for regional growth dynamics. Growth may well be related to how well local governments spend resource revenues. Connecting this assumption to Indonesia's context, if a district government uses resource revenues to expand their public investment or public spending, this could raise income.

A final explanation why resource dependence may be positively associated with GRDP in Indonesia has to do with education provision. While traditional resource curse explanations have looked at negative effects on demand for education, these have ignored potential positive effects of windfall revenues on the supply side. Some resource-rich

[49] The Ministry of Home Affairs investigates district government performance for most districts. Its ranking of districts is then used to give rewards and punishments. For the researcher, this index can provide a measure of institutional quality. In 2012, the Ministry of Administrative and Bureaucratic Reform also announced The Report of Accountability Performance to stimulate good governance implementation at district level. "Local leader commitment" and "innovation" are two important indicators for determining the highest score. For example, Banyuwangi district has been given an A index and recognized as the best governed district in Indonesia in 2016.

economies have avoided curse effects, possibly by using resource windfalls to invest more in education and human capital. In Indonesia's case, better education provision is one of the ultimate goals of public service delivery stated in most RPJMD's. It is possible that districts with resource revenues have used these to boost education and health provision beyond what they would otherwise be, creating gains in subsequent labor productivity.

Overall, the above explanations are still speculative, built from conceptual and empirical findings by studies in other locations. I have not confirmed which causal transmission channels may be responsible for the overall resource blessings found in my first chapter. Thus, to test whether some of these speculations are supported by evidence, I will investigate them more formally in my subsequent chapters.

8 Conclusion and Plan for Subsequent Chapters

So far in my analysis, I have empirically examined the direct effect of resource dependence, proxied by mining's share of GRDP or share in government revenues, on real GRDP per capita. I have examined resource dependence's effects by applying annual Fixed Effects (FE) regressions and a longer term First-Difference (FD) models. Both approaches deal with unobserved heterogeneity across districts that may affect their GRDP. In the FD case, I have also introduced various instruments for my resource dependence measures in case they are endogenous. These instruments have been both in levels (using binary and continuous historical resource abundance measures) and in changes in physical output (oil, natural gas, and coal mining) used in both instruments.

The original resource curse hypothesis was that having a high dependency on natural resources can lead to poor growth performance. Following Indonesia's districts between 2005-2015, I find no support for this hypothesis. Instead, I find that in most specifications, natural resource dependence is positively associated with local district income, particularly when it is measured as mining's share of GRDP.

My next chapter will try to shed light on the causes of these blessings. In particular, I will analyse the transmission channels through which the positive effect of resource dependence operates at the district level. The specific transmission channels I will examine are institutional quality, government spending/investment on capital, education enrollment levels, and crowding out or crowding in of non resource-based activity.

Next, while my findings in this chapter show a positive association between resource dependence and real GRDP per capita, they say nothing about how resource dependence affects other measures of living standards or development. While GDP (or equivalent) has often been used in resource curse analysis, it can oversimplify measures of regional income, and only imperfectly proxy for other outcomes of concern to policy makers. For example, an ambiguity appears when we measure GRDP based largely on the mining sector, particularly oil and gas. Because this sector is very capital intensive, and the owners of the capital may reside elsewhere, the high real GRDP per capita of such a district may not represent the "real" income that its local citizens receive. Thus, GRDP excluding oil and gas, as well as alternative outcome measures related to health, education and poverty will also be considered.

In addition to considering the effects of resource dependence on alternative outcome measures, my third chapter will also address potential spatial spillover effects of resource dependence on adjoining districts. Controlling for spatial spillovers when estimating resource effects becomes more important as the unit of observation moves from nations (in between-country studies), to fine-grained districts. It may be that the estimated resource effects are heighten or diminished after spillover effects are controlled. (The timeline for this work is given in Appendix 7).

9 Acknowledgements

I would like to thank my supervisor Assoc. Prof. Jeremy Clark for his remarkable guidance during this first chapter, and in particular, for his research funding to facilitate mapping from historical resource sites to districts. I also thank my other supervisor, Dr Andrea Menclova, for her valuable comments on this chapter. My thanks also go to Prof. Bob Reed who allowed me to attend his econometrics class. I also thank Aditya Saputra and Adi Ramadhani, for their assistance in mapping from historical resource sites to districts. I thank my wife, Vivi, and my son, Zidan, who are patiently accompanying and supporting me during my work on this chapter. Finally, I also wish to thank the Indonesia Endowment Fund for Education (LPDP), and the Indonesian Ministry of Finance for providing the scholarship to study at the University of Canterbury.

10 References

Aden, Jean. 2001. "Decentralization of Natural Resource Sectors in Indonesia: Opportunities and Risks." 23148. EASES Discussion Paper Series.

Alexeev, Michael, and Robert Conrad. 2011. "The Natural Resource Curse and Economic

Transition." *Economic Systems* 35 (4). Elsevier B.V.: 445–61. doi:10.1016/j.ecosys.2010.10.003.

———. 2016. "The Elusive Curse of Oil." *The Review of Economics and Statistics* 91 (3): 586–98.

Aragón, By Fernando M, and Juan Pablo Rud. 2013. "Natural Resources and Local Communities : Evidence from a Peruvian Gold Mine." *American Economic Journal: Economic Policy* 5 (2): 1–25.

Aragona, Fernando M., Punam Chuhan-Pole, and Bryan Christopher Land. 2015. "The Local Economic Impacts of Resource Abundance: What Have We Learned?" 7263. Policy Research Working Paper. http://econ.worldbank.org.

Arezki, Rabah, and Frederick van der Ploeg. 2011. "Do Natural Resources Depress Income per Capita?" *Review of Development Economics* 15 (3): 504–21. doi:10.1111/j.1467-9361.2011.00623.x.

Auty, Richard M. 1994. "Industrial Policy Reform in Six Large Newly Industrializing Countries: The Resource Curse Thesis." *World Development* 22 (1): 11–26. doi:10.1016/0305-750X(94)90165-1.

Badeeb, Ramez Abubakr, Hooi Hooi Lean, and Jeremy Clark. 2017. "The Evolution of the Natural Resource Curse Thesis: A Critical Literature Survey." *Resources Policy* 51 (December 2016). Elsevier: 123–34. doi:10.1016/j.resourpol.2016.10.015.

Barbier, Edward B. 2005. *Natural Resources and Economic Development*. First Edit. Cambridge Unibersity Press.

Baum, Christopher F, Mark E Schaffer, and Steven Stillman. 2007. "Enhanced Routines for Instrumental Variables / GMM Estimation and Testing," no. 667: 1–38.

Bee, Ooi Jin. 1982. *The Petroleum Resources of Indonesia*. First Edit. Kuala Lumpur: Oxford University Press.

Bellemare, Marc F, Takaaki Masaki, and Thomas B Pepinsky. 2015. "Lagged Explanatory Variables and the Estimation of Causal Effects ∗."

Betz, Michael R., Mark D. Partridge, Michael Farren, and Linda Lobao. 2015. "Coal Mining, Economic Development, and the Natural Resources Curse." *Energy Economics* 50. Elsevier B.V.: 105–16. doi:10.1016/j.eneco.2015.04.005.

Bjorvatn, Kjetil, Mohammad Reza Farzanegan, and Friedrich Schneider. 2012. "Resource Curse and Power Balance: Evidence from Oil-Rich Countries." *World Development* 40 (7). Elsevier Ltd: 1308–16. doi:10.1016/j.worlddev.2012.03.003.

Boyce, John R., and J. C. Herbert Emery. 2011. "Is a Negative Correlation between Resource Abundance and Growth Sufficient Evidence That There Is A 'resource Curse'?" *Resources Policy* 36 (1). Elsevier: 1–13. doi:10.1016/j.resourpol.2010.08.004.

Brunnschweiler, Christa N. 2008. "Cursing the Blessings? Natural Resource Abundance, Institutions, and Economic Growth." *World Development* 36 (3): 399–419. doi:10.1016/j.worlddev.2007.03.004.

Brunnschweiler, Christa N., and Erwin H. Bulte. 2008. "The Resource Curse Revisited and Revised: A Tale of Paradoxes and Red Herrings." *Journal of Environmental Economics and Management* 55 (3): 248–64. doi:10.1016/j.jeem.2007.08.004.

Bulte, Erwin H., Richard Damania, and Robert T. Deacon. 2005. "Resource Intensity, Institutions, and Development." *World Development* 33 (7): 1029–44. doi:10.1016/j.worlddev.2005.04.004.

Caselli, Francesco, and Guy Michaels. 2013. "Do Oil Windfalls Improve Living Standards? Evidence from Brazil." *American Economic Journal: Applied Economics* 5 (1): 208–38. doi:10.1257/app.5.1.208.

Chandra, Wendy. 2012. "The Impact of Dependency on Primary Commodity on Indonesia Economic Growth."

Collier, Paul, and Benedikt Goderis. 2009. "Commodity Prices, Growth, and the Natural Resource Curse: Reconciling a Conundrum." 17315. *MPRA Paper No. 17315*. MPRA. http://users.ox.ac.uk/~econpco/research/pdfs/CommodityPricesGrowthV1-1.pdf.

Coxhead, Ian. 2007. "A New Resource Curse? Impacts of China's Boom on Comparative Advantage and Resource Dependence in Southeast Asia." *World Development* 35 (7): 1099–1119. doi:10.1016/j.worlddev.2006.10.012.

Cust, James, and Steven Poelhekke. 2015a. "The Local Economic Impacts of Natural Resource Extraction." *Annual Review of Resource Economics* 7 (1): 251–68. doi:10.1146/annurev-resource-100814-125106.

———. 2015b. "The Local Economic Impacts of Natural Resource Extraction Extraction." *Annual Review of Resource Economics* 7 (0).

Cust, James, and Ridwan D Rusli. 2016. "Disentangling the Effects of Resource Extraction : Quantifying Local Government and Project Multipliers."

Davis, Graham A. 1995. "Learning to Love the Dutch Disease: Evidence from the Mineral Economies." *World Development* 23 (10): 1765–79. doi:10.1016/0305-750X(95)00071-J.

Davoodi, Hamid, and Heng-fu Zou. 1998. "Fiscal Decentralization and Economic Growth : A Cross-Country Study *." *Journal of Urban Economics* 43: 244–57.

Doraisami, Anita. 2015. "Has Malasyia Really Escaped the Resources Curse? A Closer Look at the Political Economy of Oil Revenue Management and Expenditures." *Resources Policy* 45. Elsevier: 98–108. doi:10.1016/j.resourpol.2015.03.008.

Douglas, Stratford, and Anne Walker. 2016. "Coal Mining and the Resource Curse in the Eastern United States." *Journal of Regional Science* 0 (0): 1–23. doi:10.1111/jors.12310.

Edwards, Ryan B. 2016. "Mining Away the Preston Curve." *World Development* 78. Elsevier Ltd: 22–36. doi:10.1016/j.worlddev.2015.10.013.

Edwards, Ryan Barclay. 2016. "Natural Resource Sectors and Human Development: International and Indonesian Evidence." Australian National University. https://openresearch-repository.anu.edu.au/handle/1885/101148.

Fan, Rui, Ying Fang, and Sung Y. Park. 2012. "Resource Abundance and Economic Growth in China." *China Economic Review* 23 (3). Elsevier Inc.: 704–19. doi:10.1016/j.chieco.2012.04.007.

Fleming, David A., and Thomas G. Measham. 2015. "Local Economic Impacts of an Unconventional Energy Boom: The Coal Seam Gas Industry in Australia." *Australian Journal of Agricultural and Resource Economics* 59 (1): 78–94. doi:10.1111/1467-8489.12043.

Fleming, David A., Thomas G. Measham, and Dusan Paredes. 2015. "Understanding the Resource Curse (or Blessing) across National and Regional Scales: Theory, Empirical Challenges and an Application." *Australian Journal of Agricultural and Resource Economics* 59 (4): 624–39. doi:10.1111/1467-8489.12118.

Frankel, Jeffrey A. 2010. "The Natural Resource Curse: A Survey." 15836. *NBER Working Paper Series*. doi:10.2139/ssrn.1565588.

Friederich, Mike C., and Theo van Leeuwen. 2017. "A Review of the History of Coal Exploration, Discovery and Production in Indonesia: The Interplay of Legal Framework, Coal Geology and Exploration Strategy." *International Journal of Coal Geology*. Elsevier B.V. doi:10.1016/j.coal.2017.04.007.

Gerelmaa, Lkhagva, and Koji Kotani. 2013. "Economics & Management Series Further Investigation of Natural Resources and Eco Nomic Growth: Do Natural Resources Depress Economic Growth? Further Investigation of Natural Resources and Economic Growth: Do Natural Resources Depress Economic Growth?" *International University of Javan* 7 (October). Elsevier: 312–21. doi:10.1016/j.resourpol.2016.10.004.

Guo, J, X Zheng, and F Song. 2016. "The Resource Curse and Its Transmission Channels: An Empirical Investigation of Chinese Cities' Panel Data." *Emerging Markets Finance and Trade*, no. June: 1325–34. doi:10.1080/1540496X.2016.1152812.

Gylfason, Thorvaldur. 2001a. "Natural Resources, Education, and Economic Development." *European Economic Review* 45 (4–6): 847–59. doi:10.1016/S0014-2921(01)00127-1.

———. 2001b. "Natural Resources and Economic Growth: What Is the Connection?" 530. CESifo. Munich, Germany.

Hajkowicz, Stefan A., Sonja Heyenga, and Kieren Moffat. 2011. "The Relationship between Mining and Socio-Economic Well Being in Australia's Regions." *Resources Policy* 36 (1). Elsevier: 30–38. doi:10.1016/j.resourpol.2010.08.007.

Hill, Hal, Budy P. Resosudarmo, and Yogi Vidyattama*. 2008. "Indonesia's Changing Economic Geography." *Bulletin of Indonesian Economic Studies* 44 (3): 407–35. doi:10.1080/00074910802395344.

Humphreys, Macartan, Jeffrey D. Sachs, and Joseph E. Stiglitz. 2007. *Escaping the Resource Curse*. New York: Columbia University Press.

James, Alex, and David Aadland. 2011. "The Curse of Natural Resources: An Empirical Investigation of U.S. Counties." *Resource and Energy Economics* 33 (2). Elsevier B.V.: 440–53. doi:10.1016/j.reseneeco.2010.05.006.

James, Alexander. 2015. “The Resource Curse: A Statistical Mirage?” *Journal of Development Economics* 114. Elsevier B.V.: 55–63. doi:10.1016/j.jdeveco.2014.10.006.

John, Jonathan di. 2011. “Is There Really a Resource Curse? A Critical Survey of Theory and Evidence.” *Global Governance* 17 (2): 167–84.

Komarulzaman, Ahmad, and Armida S Alisjahbana. 2006. “Testing the Natural Resource Curse Hypothesis in Indonesia : Evidence at the Regional Level.” *Working Paper in Economics and Development Studies*, no. 200602.

Kunchu, J A B, T Sarmidi, Md A H S Nor, and I Yussof. 2016. “New Evidence on Natural Resource Curse for OIC and Non OIC Countries.” *Pertanika Journal of Social Science and Humanities* 24 (4): 1767–92.

Lederman, Daniel, and William F Maloney. 2003. “Trade Structure and Growth.” 3025.

Lederman, Daniel, and William F. Maloney. 2008. “In Search of the Missing Resource Curse.” *Economia* 9 (November): 1–56. doi:10.1353/eco.0.0012.

Leeuwen, Theo M Van. 1994. “25 Years of Mineral Exploration and Discovery in Indonesia.” *Journal of Geochemical Exploration* 50: 13–90.

Lei, Yalin, Na Cui, and Dongyang Pan. 2013. “Economic and Social Effects Analysis of Mineral Development in China and Policy Implications.” *Resources Policy* 38 (4). Elsevier: 448–57. doi:10.1016/j.resourpol.2013.06.005.

Libman, Alexander. 2013. “Natural Resources and Sub-National Economic Performance: Does Sub-National Democracy Matter?” *Energy Economics* 37. Elsevier B.V.: 82–99. doi:10.1016/j.eneco.2013.02.003.

Loayza, Norman, and Jamele Rigolini. 2016. “The Local Impact of Mining on Poverty and Inequality: Evidence from the Commodity Boom in Peru.” *World Development* 84. Elsevier Ltd: 219–34. doi:10.1016/j.worlddev.2016.03.005.

Mcmahon, Gary, and Susana Moreira. 2014. “The Contribution of the Mining Sector to Socioeconomic and Human Development.” 87298. Extractive Industries for Development Series.

Mehlum, Halvor, Karl Moene, and Ragnar Torvik. 2006. “Institutions and the Resource Curse.” *Economic Journal* 116 (508): 1–20. doi:10.1111/j.1468-0297.2006.01045.x.

North, D. C. 1982. *Economics in the Long View: Essays in Honour of W.W. Rostow*. Edited by Charles P. Kindleberger and Guido di Tella. *The Theoritical Tools of the Economic Historian*. Volume I. The MacMillan Press LTD. doi:10.1017/CBO9781107415324.004.

Ouoba, Youmanli. 2016. “Natural Resources: Funds and Economic Performance of Resource-Rich Countries.” *Resources Policy* 50. Elsevier: 108–16. doi:10.1016/j.resourpol.2016.09.003.

Papyrakis, Elissaios. 2016. “The Resource Curse - What Have We Learned from Two Decades of Intensive Research: Introduction to the Special Issue.” *Journal of Development Studies* 53 (April). Routledge: 1–11.

doi:10.1080/00220388.2016.1160070.

Papyrakis, Elissaios, and Reyer Gerlagh. 2004. “The Resource Curse Hypothesis and Its Transmission Channels.” *Journal of Comparative Economics* 32 (1): 181–93. doi:10.1016/j.jce.2003.11.002.

———. 2007. “Resource Abundance and Economic Growth in the United States.” *European Economic Review* 51 (4): 1011–39. doi:10.1016/j.euroecorev.2006.04.001.

Ploeg, Frederick Van Der. 2011. “Natural Resources: Curse or Blessing?” *Journal of Economic Literature* 49 (2): 366–420. doi:10.1257/jel.49.2.366.

Ploeg, Frederick van der, and Steven Poelhekke. 2016. “The Impact of Natural Resources: Survey of Recent Quantitative Evidence.” *Journal of Development Studies* 53 (April). Routledge: 1–12. doi:10.1080/00220388.2016.1160069.

Rosser, Andrew. 2007. “Escaping the Resource Curse: The Case of Indonesia.” *Journal of Contemporary Asia* 37 (773564139): 38–58. doi:10.1080/00472330601104557.

Sachs, Jeffrey D., and Andrew M. Warner. 1995. “Natural Resource Abundance and Economic Growth.” 5398. *NBER Working Paper Series*. Vol. 3. doi:10.3386/w5398.

Schaffer, Mark E, Christopher F Baum, and Steven Stillman. 2003. “Instrumental Variables and GMM : Estimation and Testing.” *The Stata Journal* 3 (1): 1–31.

Sovacool, Benjamin K. 2010. “The Political Economy of Oil and Gas in Southeast Asia: Heading towards the Natural Resource Curse?” *The Pacific Review* 23 (2): 225–59. doi:10.1080/09512741003624484.

Stiglitz, Joseph, and Joseph Stiglitz. 1974. “Growth with Exhaustible Natural Resources : Efficient and Optimal Growth Paths '".” *The Review of Economic Studies* 41: 123–37.

Stijns, Jean-Philippe C. 2000. “Natural Resource Abundance and Economic Growth Revisited.” *Resources Policy* 30 (2): 1–40. doi:10.1016/j.resourpol.2005.05.001.

Torvik, Ragnar. 2009. “Why Do Some Resource-Abundant Countries Succeed While Others Do Not?” *Oxford Review of Economic Policy* 25 (2): 241–56. doi:10.1093/oxrep/grp015.

Usui, Norio. 1997. “Dutch Disease and Policy Adjustments to the Oil Boom: A Comparative Study of Indonesia and Mexico.” *Resources Policy* 23 (4): 151–62. doi:10.1016/S0301-4207(97)00023-8.

Walker, AW. 2013. “An Empirical Analysis of Resource Curse and the Educational Attainment Channel in the Appalachian Region.” *Available at SSRN 2165375*. http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2165375.

Weber, Jeremy G. 2012. “The Effects of a Natural Gas Boom on Employment and Income in Colorado, Texas, and Wyoming.” *Energy Economics* 34 (5). Elsevier B.V.: 1580–88. doi:10.1016/j.eneco.2011.11.013.

———. 2014. “A Decade of Natural Gas Development: The Makings of a Resource Curse?” *Resource and Energy Economics* 37. Elsevier B.V.: 168–83. doi:10.1016/j.reseneeco.2013.11.013.

Wooldridge, Jeffrey M. 2016. *Introductory Econometrics, 6e*. Cengage Learning.

Wright, Gavin, and Jesse Czelusta. 2004. “The Myth of the Resource Curse.” *Challenge* 47 (2): 6–38. doi:Article.

Wu, Sanmang, and Yalin Lei. 2016. “Study on the Mechanism of Energy Abundance and Its Effect on Sustainable Growth in Regional Economies: A Case Study in China.” *Resources Policy* 47. Elsevier: 1–8. doi:10.1016/j.resourpol.2015.10.006.

Zhuang, Yuyi, and Guang Zhang. 2016. “Natural Resources, Rent Dependence, and Public Goods Provision in China: Evidence from Shanxi’s County-Level Governments.” *The Journal of Chinese Sociology* 3 (1). The Journal of Chinese Sociology: 20. doi:10.1186/s40711-016-0040-3.

Table 3 Descriptive statistics for all districts/years pooled

Variable	Obs	Mean	Std. Dev.	Min	Max
Real GRDP per capita (in logs)	4290	4.139377	0.690165	1.951301	7.683826
Mining Dependence GRDP	4290	0.090965	0.179296	0	0.954621
Mining Revenue Dependence	4290	0.052757	0.123603	0	0.872433
Oil&gas revenue Dependence	4290	0.03799	0.106686	0	0.871858
Coal Revenue Dependence	4290	0.014772	0.044392	0	0.550445
Earthquake	4290	0.05990	0.25257	0	3
Labor force participation rate	4290	0.645012	0.095994	0.1949	0.988
Households with electricity	4290	0.874352	0.189802	0.0028	1

Table 4 Descriptive Statistics for First Difference Model

Variable	Obs	Mean	Std. Dev.	Min	Max
Δ Real GRDP per capita (in logs)	390	0.413809	0.344784	-0.85163	2.685206
ΔMining Dependence	390	0.011747	0.141974	-0.61372	0.795062
ΔMining Revenue	390	-0.01322	0.084406	-0.52328	0.255585
ΔOilgas Revenue	390	-0.02868	0.091328	-0.52781	0.224138
ΔCoal Revenue	390	0.015421	0.047512	-0.11861	0.358853
Earthquake	390	0.464103	0.936269	0	7
ΔLabor force partic.rate	390	0.067598	0.112044	-0.1906	0.4427
Population, 2005 (in logs)	390	12.72085	1.028841	9.450066	15.227
GRDP per capita, 2005 (in logs)	390	3.937389	0.703827	1.951301	7.683826
DURBAN	390	0.207692	0.406176	0	1
DJAVA	390	0.302564	0.459958	0	1
Instruments					
Oilgas_continous	390	0.153846	0.660138	0	7
Coal deposit_continous	390	3.660233	14.32723	0	94.2137
Oilgas_binary	390	0.058974	0.235879	0	1
Coal deposit_binary	390	0.066667	0.249764	0	1
Δoil production (thousand barrels)	390	-103.164	3805.166	-22751.3	64381.61
Δgas production (MMBTU)	390	267.5436	31094.97	-402891	378035.7
Δ coal production (IDR)	390	92.61852	508.369	-45.2773	5845.853

Table 5 Panel Fixed Effect Model of the Effect of Resource Dependence on real GRDP per capita

Dependent Variable: GRDP per capita (in logs)

VARIABLES	(1) FE1	(2) FE2	(3) FE3	(4) FE4
Mining Dependence	0.406***			
	(0.113)			
Oil&Gas Revenue		0.167		
		(0.170)		
Coal revenue			-0.421*	
			(0.241)	
Mining Revenue				0.0353
				(0.132)
Earthquake	-0.0159*	-0.0164*	-0.0167*	-0.0168*
	(0.00834)	(0.00873)	(0.00876)	(0.00876)
Labor force	0.105	0.117	0.104	0.117
	(0.0784)	(0.0776)	(0.0784)	(0.0771)
Household elect.	-0.0728	-0.00834	-0.00453	-0.00701
	(0.0888)	(0.0921)	(0.0929)	(0.0922)
Constant	3.891***	3.867***	3.879***	3.869***
	(0.0752)	(0.0763)	(0.0761)	(0.0764)
Year Effect	Yes	Yes	Yes	Yes
District Fixed Effects	Yes	Yes	Yes	Yes
Observations	4,290	4,290	4,290	4,290
R-squared	0.492	0.478	0.479	0.478
Number of DISTRICT1	390	390	390	390

Notes:

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 6 Effects of resource dependence on change in real GRDP per capita (in logs) in First Difference form (without instruments)

Dependent Variable: ΔGRDP per capita in logs

VARIABLES	(1)	(2)	(3)	(4)
ΔMining Dependence	0.738***			
	(0.190)			
ΔOilgas Revenue		-0.160		
		(0.473)		
ΔCoal Revenue			0.469	
			(0.522)	
Δ Mining Revenue				-0.0757
				(0.389)
Earthquake	-0.0325**	-0.0336***	-0.0319***	-0.0341***
	(0.0133)	(0.0118)	(0.0118)	(0.0122)
ΔLabor force partic.rate	0.0369	0.0254	0.0730	0.0195
	(0.186)	(0.192)	(0.189)	(0.206)
GRDP per capita, 2005 (in logs)	-0.113***	-0.148***	-0.150***	-0.141***
	(0.0318)	(0.0366)	(0.0342)	(0.0294)
Population, 2005 (in logs)	0.00758	0.000282	0.00390	0.000152
	(0.0233)	(0.0258)	(0.0255)	(0.0265)
DURBAN	0.0455	0.0402	0.0473	0.0364
	(0.0421)	(0.0420)	(0.0447)	(0.0438)
DJAVA	0.0845*	0.0380	0.0364	0.0340
	(0.0483)	(0.0467)	(0.0437)	(0.0451)
Constant	0.730**	0.983***	0.938***	0.961***
	(0.290)	(0.357)	(0.328)	(0.350)
Observations	390	390	390	390
R-squared	0.158	0.076	0.078	0.075

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 7 Effect of changes in resource dependence on growth in GRDP per capita with abundance IV's (continous+changes of physical production), First Difference Model

Dependent Variable: ΔGRDP per capita (in logs)

	(1)	(1′)	(2)	(2′)	(3)	(3′)	(4)	(4′)
VARIABLES	**OLS**	**IV-GMM**	**OLS**	**IV-GMM**	**OLS**	**IV-GMM**	**OLS**	**IV-GMM**
ΔMining Dependence	0.738***	1.356***						
	(0.190)	(0.444)						
ΔMining Revenue			-0.0757	1.164**				
			(0.389)	(0.581)				
ΔOilgas Revenue					-0.160	1.765**		
					(0.473)	(0.810)		
ΔCoal Revenue							0.469	-0.696
							(0.522)	(0.645)
Earthquake	-0.0325**	-0.0306*	-0.0341***	-0.0264**	-0.0336***	-0.0347***	-0.0319***	-0.0373***
	(0.0133)	(0.0181)	(0.0122)	(0.0111)	(0.0118)	(0.0131)	(0.0118)	(0.0122)
ΔLabor force partic.rate	0.0369	0.0589	0.0195	0.215	0.0254	0.0513	0.0730	-0.0445
	(0.186)	(0.189)	(0.206)	(0.179)	(0.192)	(0.234)	(0.189)	(0.201)
GRDP per capita, 2005 (in logs)	-0.113***	-0.111***	-0.141***	-0.0973**	-0.148***	-0.0350	-0.150***	-0.119***
	(0.0318)	(0.0355)	(0.0294)	(0.0394)	(0.0366)	(0.0663)	(0.0342)	(0.0386)
Population, 2005 (in logs)	0.00758	0.0234	0.000152	0.0315	0.000282	0.0212	0.00390	-0.00568
	(0.0233)	(0.0203)	(0.0265)	(0.0212)	(0.0258)	(0.0263)	(0.0255)	(0.0254)
DURBAN	0.0455	0.0751*	0.0364	0.0479	0.0402	0.0119	0.0473	0.0181
	(0.0421)	(0.0415)	(0.0438)	(0.0447)	(0.0420)	(0.0585)	(0.0447)	(0.0474)
DJAVA	0.0845*	0.114*	0.0340	-0.0222	0.0380	-0.0477	0.0364	0.0291
	(0.0483)	(0.0598)	(0.0451)	(0.0419)	(0.0467)	(0.0496)	(0.0437)	(0.0433)
Constant	0.730**	0.487*	0.961***	0.397	0.983***	0.351	0.938***	0.973***
	(0.290)	(0.282)	(0.350)	(0.256)	(0.357)	(0.323)	(0.328)	(0.320)
Cragg-Donald Wald F statistic		8.900		27.509		29.017		111.683

	(1)	(1′)	(2)	(2′)	(3)	(3′)	(4)	(4′)
VARIABLES	**OLS**	**IV-GMM**	**OLS**	**IV-GMM**	**OLS**	**IV-GMM**	**OLS**	**IV-GMM**
Kleibergen-Paap rk Wald F statistic		16.834		14.807		27.754		25.347
Hansen J statistic, P-value		0.2228		0.1486		0.3552		0.6354
Endogeneity test, P value		0.2481		0.1081		0.0149		0.0178
Observations	390	390	390	390	390	390	390	390
R-squared	0.158	0.103	0.074	-0.001	0.075	-0.107	0.077	0.065

Note: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 8 Effect of changes in resource dependence on growth in GRDP per capita with abundance IV's (binary+changes of physical production), First Difference Model

Dependent Variable: ΔGRDP per capita in logs

	(1)	(1′)	(2)	(2′)	(3)	(3′)	(4)	(4′)
VARIABLES	**OLS**	**IV-GMM**	**OLS**	**IV-GMM**	**OLS**	**IV-GMM**	**OLS**	**IV-GMM**
ΔMining Dependence	0.738***	1.143**						
	(0.190)	(0.579)						
ΔMining Revenue			-0.0757	1.059*				
			(0.389)	(0.637)				
ΔOilgas Revenue					-0.160	1.359*		
					(0.473)	(0.710)		
ΔCoal Revenue							0.469	-0.456
							(0.522)	(0.708)
Earthquake	-0.0325**	-0.0310*	-0.0341***	-0.0273**	-0.0336***	-0.0341***	-0.0319***	-0.0352***
	(0.0133)	(0.0181)	(0.0122)	(0.0113)	(0.0118)	(0.0124)	(0.0118)	(0.0121)
ΔLabor force partic.rate	0.0369	0.135	0.0195	0.237	0.0254	0.0677	0.0730	-0.00293
	(0.186)	(0.186)	(0.206)	(0.173)	(0.192)	(0.218)	(0.189)	(0.202)
GRDP per capita, 2005 (in logs)	-0.113***	-0.108***	-0.141***	-0.0872**	-0.148***	-0.0559	-0.150***	-0.128***
	(0.0318)	(0.0351)	(0.0294)	(0.0391)	(0.0366)	(0.0563)	(0.0342)	(0.0384)
Population, 2005 (in logs)	0.00758	0.0286	0.000152	0.0308	0.000282	0.0200	0.00390	0.000595
	(0.0233)	(0.0199)	(0.0265)	(0.0209)	(0.0258)	(0.0247)	(0.0255)	(0.0256)
DURBAN	0.0455	0.0687	0.0364	0.0392	0.0402	0.0186	0.0473	0.0299
	(0.0421)	(0.0421)	(0.0438)	(0.0436)	(0.0420)	(0.0526)	(0.0447)	(0.0470)
DJAVA	0.0845*	0.0933	0.0340	-0.0186	0.0380	-0.0322	0.0364	0.0253
	(0.0483)	(0.0658)	(0.0451)	(0.0430)	(0.0467)	(0.0472)	(0.0437)	(0.0434)
Constant	0.730**	0.415	0.961***	0.368	0.983***	0.430	0.938***	0.919***
	(0.290)	(0.281)	(0.350)	(0.257)	(0.357)	(0.293)	(0.328)	(0.322)
Cragg-Donald Wald F statistic		8.108		31.065		41.389		115.597

	(1)	(1′)	(2)	(2′)	(3)	(3′)	(4)	(4′)
VARIABLES	**OLS**	**IV-GMM**	**OLS**	**IV-GMM**	**OLS**	**IV-GMM**	**OLS**	**IV-GMM**
Kleibergen-Paap rk Wald F statistic		7.759		13.896		30.976		27.580
Hansen J statistic, P-value		0.2691		0.4702		0.4555		0.6313
Endogeneity test, P value		0.6970		0.0630		0.0180		0.1674
Observations	390	390	390	390	390	390	390	390
R-squared	0.158	0.136	0.074	0.012	0.075	-0.036	0.077	0.072

Note: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

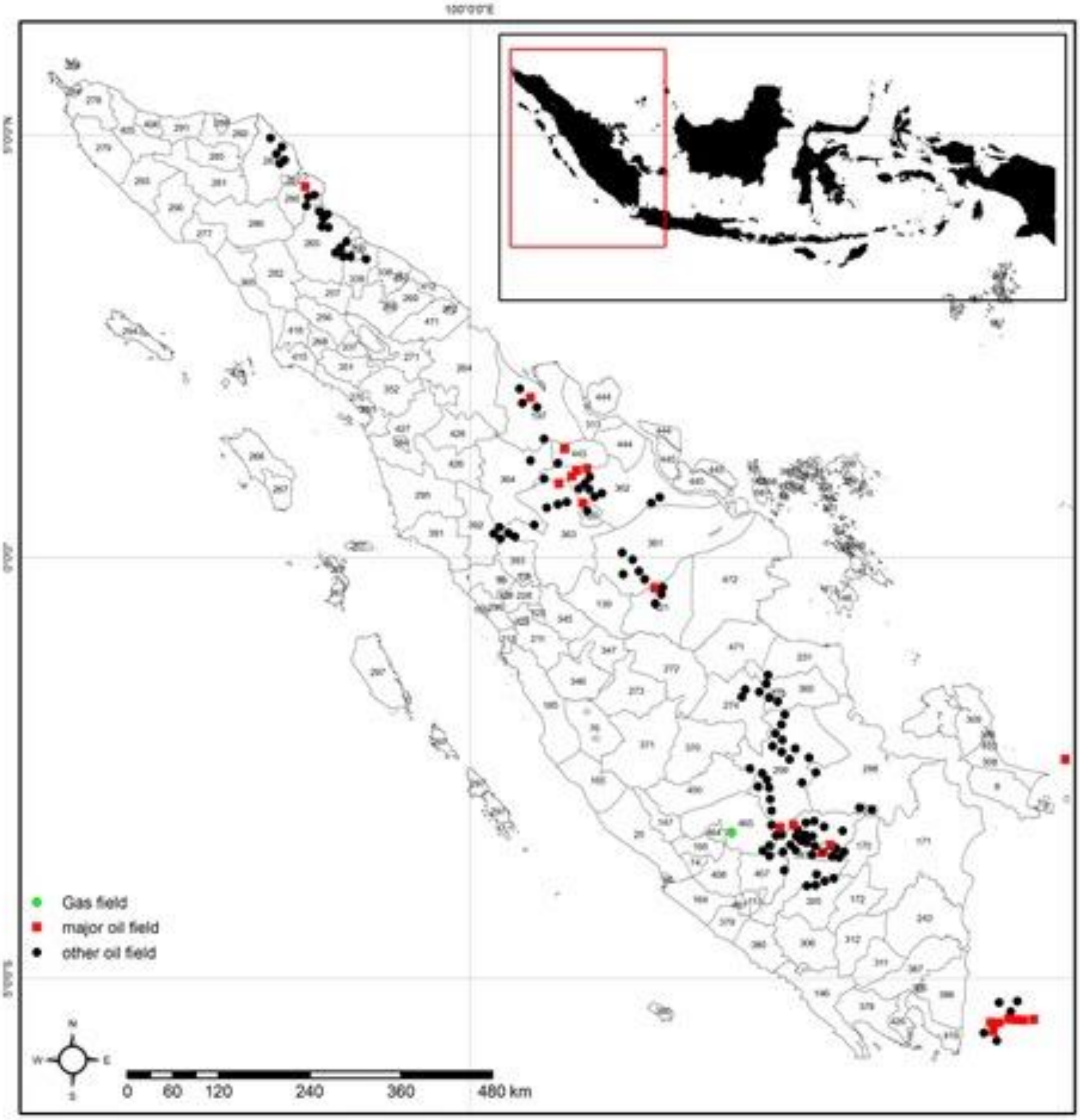
Appendix 1: Definition of Variables and Data Sources

Variable	Definition	Source
Real GRDP per capita	Natural logarithm of the GRDP (Real Gross Regional Domestic Product) divided by total population at district level	INDO DAPOER World Bank, The Indonesian National Statistical Agency (BPS)
Earthquake	The number of earthquake events at the district level	Indonesian National Board for Disaster Management (BNPB). Can be accessed online here: http://bnpb.cloud/bnpb/tabel1
Labor force participation rate	Natural logarithm of the participation of labor force in the number of people at working age (15-65)	INDO DAPOER World Bank, BPS
LGRDP per capita '05	Natural logarithm of initial GRDP percapita in 2005	INDO DAPOER World Bank, BPS
LPOP_05	Natural logarithm of initial population in 2005	BPS
DURBAN	Dummy urban status (municipalities) = 1 if urban districts, = 0 if non-urban/rural district	Identity of urban district/municipality is taken from the Ministry of Home Affairs, the Republic of Indonesia
DJAVA	Dummy of Java Island = 1 if the districts are located on Java Island, = 0 otherwise	-
Household electricity	Percentage of households with an access to electricity.	INDO DAPOER World Bank
MINDEP	The ratio of mining GRDP to total GRDP (real)	Ministry of Finance, Republic of Indonesia; The Audit Board of the Republic of Indonesia
MINREV	The share of mining revenues, summing oil, natural gas, and coal revenues, in total government budget at district level	Ministry of Finance, Republic of Indonesia; The Audit Board of the Republic of Indonesia; BPS

Variable	Definition	Source
OILGASREV	The share of oil and natural gas revenues in total government budget, at district level	Ministry of Finance, Republic of Indonesia; The Audit Board of the Republic of Indonesia; BPS
COALREV	The share of coal and other minerals revenues in total government budget, at district level	Ministry of Finance, Republic of Indonesia; The Audit Board of the Republic of Indonesia; BPS
OILGAS BINARY	Dummy variable, = 1 if at least one major oil or gas field operated there during 1970's, = 0 otherwise.	Ooi Jin Bee (1982)
COAL BINARY	Dummy variable, =1 if at least 20% of district is covered by a "first generation" coal agreement contract during the 1970's, = 0 otherwise.	Leeuwen (1994,2017)
OILGAS CONTINOUS	The number of major and minor oil and gas fields in 1970's production period in all island in Indonesia. Major oil and natural gas fields is weigted by 1, and all minor fields are weighted by 0.25. So, if in district A has a 10 minor oil/gas fields location, therefore: $District_A = 10 \times 0.25 = 2.5$	Ooi Jin Bee (1982)
COAL CONTINOUS	The share of coal deposit areas (showed by first generation coal agreement contract introduced by Leeuwen (1994, 2017)) of total area of respective district.	Leeuwen (1994,2017)

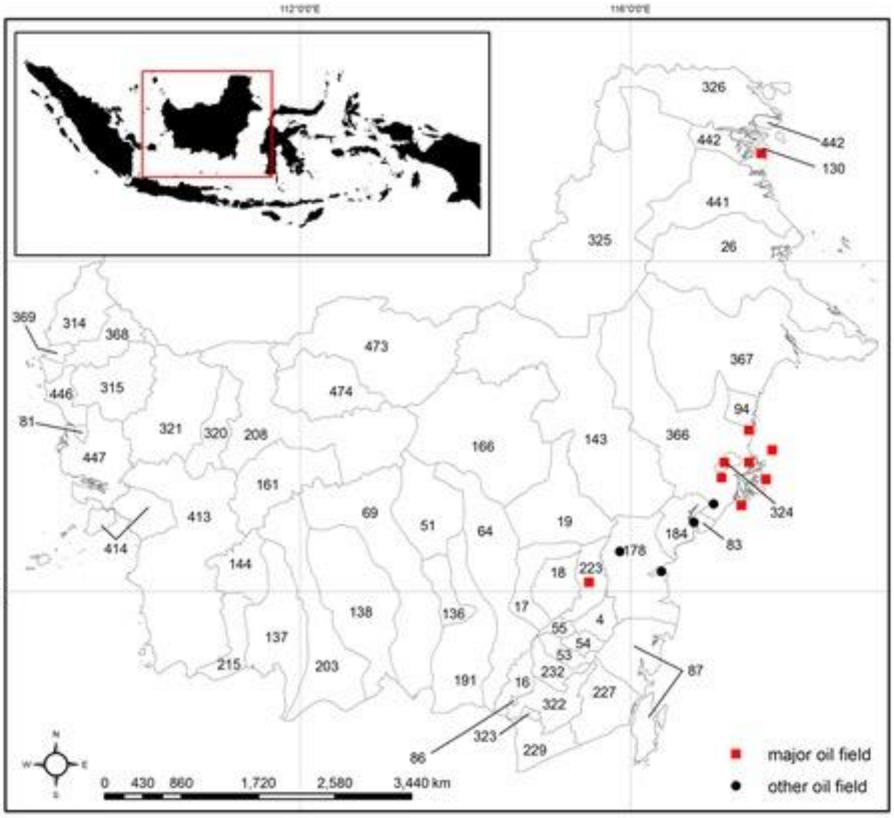
Variable	Definition	Source
ΔGRDP PER CAPITA	The natural logarithm of difference of real GRDP per capita, formulated as: ΔGRDP per capita $= ln(\frac{GRDP_{percapita,2015}}{GRDP_{percapita,2006}})$	INDO DAPOER World Bank, BPS
ΔMINING DEPENDENCE	The difference of mining dependence between 2015 and 2006, formulated as: $(MINDEP_{2015}) - (MINDEP_{2006})$	Ministry of Finance, Republic of Indonesia; The Audit Board of the Republic of Indonesia
ΔMINING REVENUE	The difference in mining revenue shares, between 2015 and 2006	Ministry of Finance, Republic of Indonesia; The Audit Board of the Republic of Indonesia
ΔOILGAS REVENUE	The difference in oil and gas revenue shares, between 2015 and 2006	Ministry of Finance, Republic of Indonesia; The Audit Board of the Republic of Indonesia
ΔCOAL REVENUE	The difference in coal revenue shares, between 2015 and 2006	Ministry of Finance, Republic of Indonesia; The Audit Board of the Republic of Indonesia
ΔLABOR FORCE PARTIC.RATE	The change in labor force participation rate between 2015 and 2006	INDO DAPOER World Bank, BPS
ΔPOPULATION (LOGS)	The change in the population (in logs) between 2015 and 2006	INDO DAPOER World Bank, BPS
Δ COAL PRODUCTION	The change in coal land rents and royalties between 2015 and 2006	Ministry of Energy and Mineral Resources, Republic of Indonesia
ΔOIL PRODUCTION	The change in oil production (in barrels) between 2015 and 2006	Ministry of Energy and Mineral Resources, Republic of Indonesia
ΔGAS PRODUCTION	The change in natural gas production (in MMBTU) between 2015 and 2006	Ministry of Energy and Mineral Resources, Republic of Indonesia

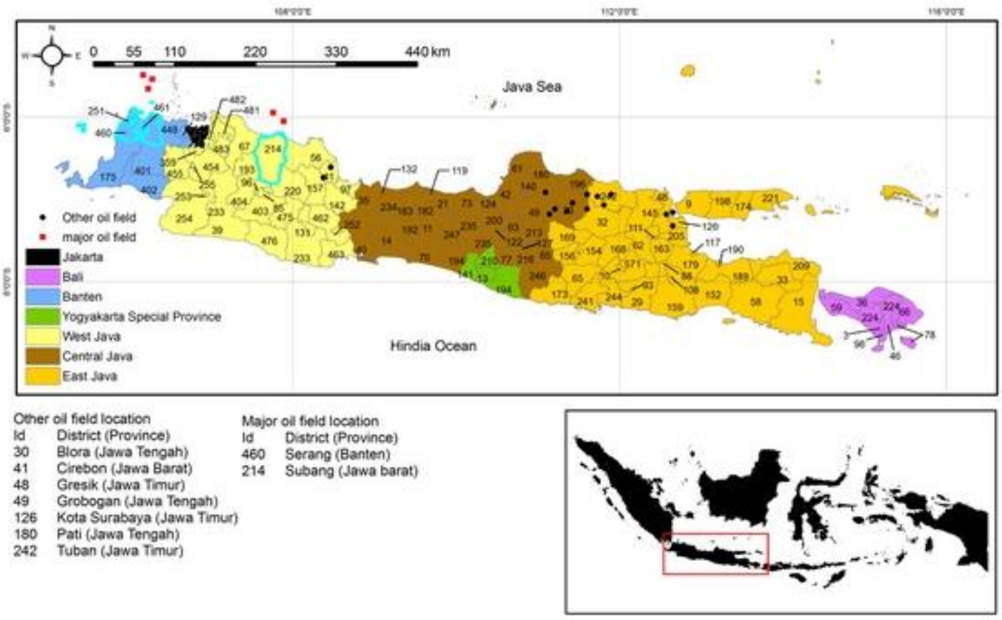
Appendix 2: The Distribution of Major and Minor Oil Fields (Including Natural Gas) in Sumatra Island in 1970's



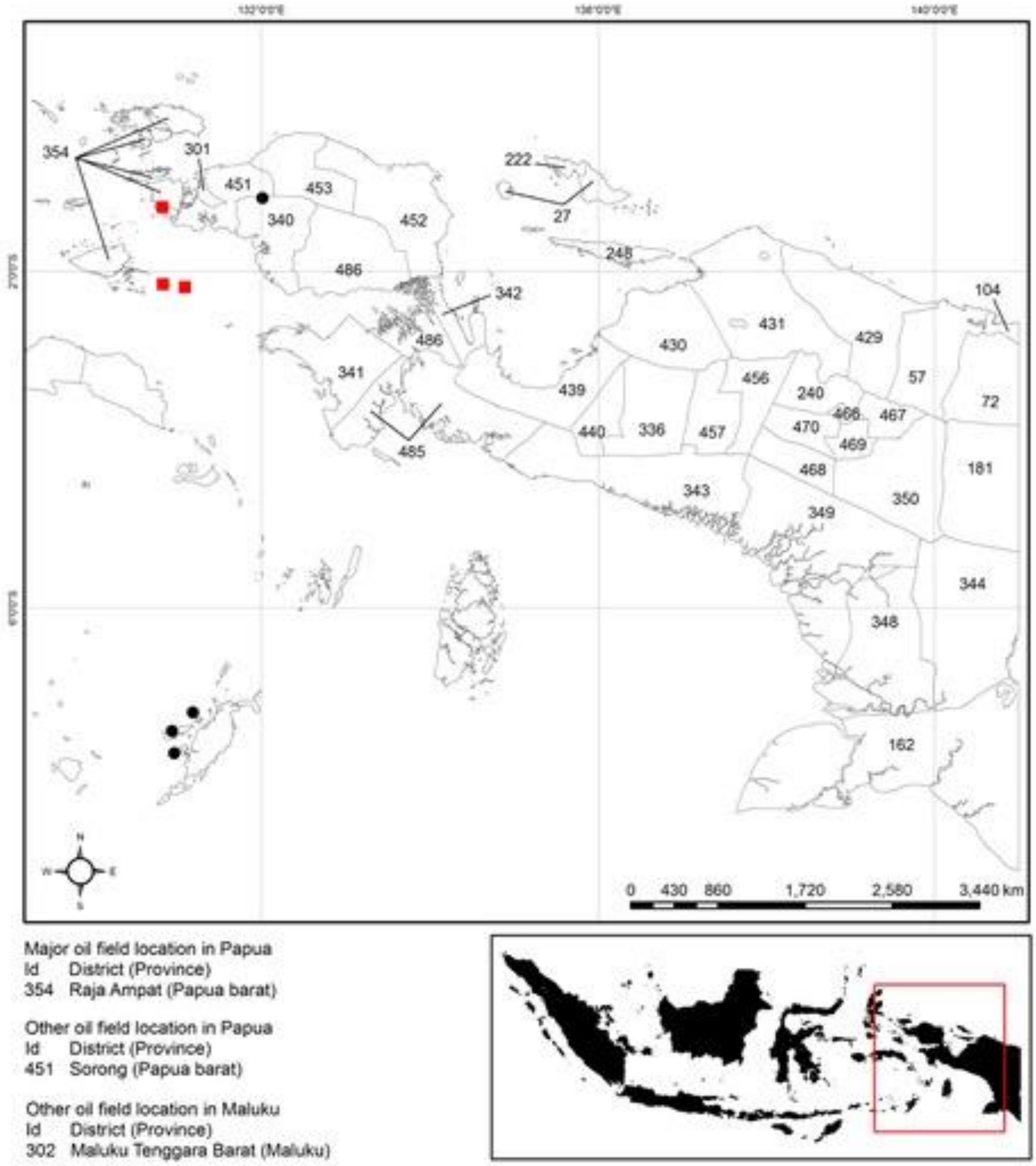
Source: Ooi Jin Bee (1982), mapped to 2003 District Boundaries

Appendix 3: The Distribution of Major and Minor Oil Fields (Including Natural Gas) in Kalimantan and Java Islands in the 1970's

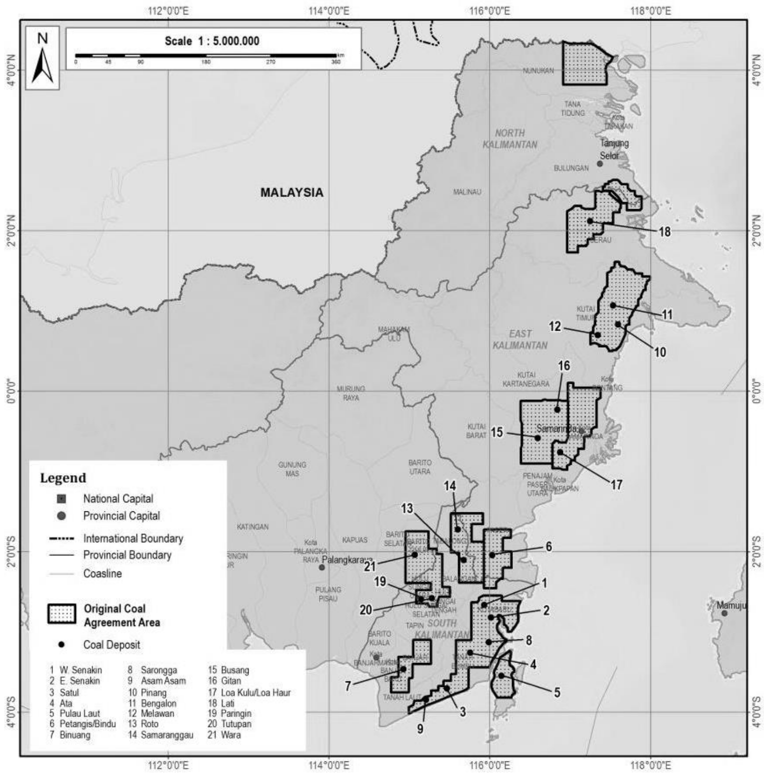


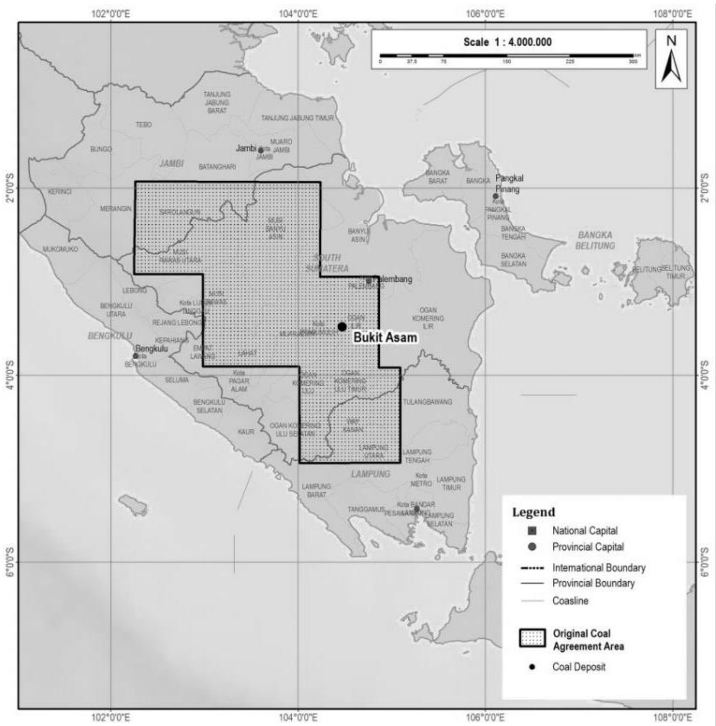


Source: Ooi Jin Bee (1982), mapped to 2003 District Boundaries


354
301
451
453
340
452
486
222
27
248
342
104
431
430
429
57
72
341
486
439
456
240
466
467
440
336
457
470
469
485
468
181
343
350
349
344
348
162
0 430 860 1,720 2,580 3,440 km
Major oil field location in Papua
Id District (Province)
354 Raja Ampat (Papua barat)
Other oil field location in Papua
Id District (Province)
451 Sorong (Papua barat)
Other oil field location in Maluku
Id District (Province)
302 Maluku Tenggara Barat (Maluku)

Appendix 4: The Location of Coal Deposit Based on First Generation Contract Agreements, during the 1980's, Kalimantan and Sumatra Islands





Source: Friederich & van Leeuwen (2017); Leeuwen (1994), mapped to 2003 District Boundaries

Appendix 5: Papers Finding Evidence of a Blessing Effect of the Natural Resources

No	Findings (+)	Authors	Period	Sample	Techniques	Definition of resources
1	Resource abundance (Natural resource capital) is positively correlated with average annual growth in real GDP per capita	(Gerelmaa and Kotani 2013)	1990-2010	Cross-country	OLS Regression	The log of the per capita natural resource capital data to estimate the effect of natural resource abundance on economic growth over the period between 1990 and 2010
2	Resource dependence is positively correlated with theaverage annual growth rate of the real GDP per capita	(Ouoba 2016)	1980-2010	Panel data, country	Panel data	Resource dependence is the share of total natural resource rents in GDP
4	Resource abundance [total natural capital and subsoil wealth] has a positive effect on economic growth	(Brunnschweiler 2008)	1994-2000	Cross-country	OLS and 2SLS,	Log growth of income per cpaita, average 1970-2000 (as dependent variable), resource abundance is defined as the log total natural capital (in US$) per capita, averaged over 1994-2000, and as the log of subsoil wealth (in US$) per capita, averaged 1994-2000 Resource rent is measured as a proxy for natural resource wealth.
7	Oil rent and mineral resources have a positive impact on real income for (Organization of Islamic Cooperation) OIC countries but not for non-OIC	(Kunchu et al. 2016)	1981-2010	OIC (Organization of Islamic Cooperation) countries and	GMM panel data First-differenced GMM works	Dependent variable uses GDP per capita, oil, mineral natural gas, forestry and coal as the natural resource wealth. All data are obtained from world Bank.

No	Findings (+)	Authors	Period	Sample	Techniques	Definition of resources
	countries.			non-OIC countries		
8	Resource abundance has a positive effect on growth	(Fan, Fang, and Park 2012)	1997-2005	China's prefectural-level cities, comprising 206 cities	Linear regression	Resource abundance is measured using the average fraction of mining industry (coal, oil, natural gas, metal and non-metal ores and other resources) workers compared to the total population. Growth rate is calculated as average rate of GDP per capita of city, from 1997-2005, $G_i = \ln(\frac{Y_{2005,i}}{Y_{1997,i}})$
10	Oil and natural gas have a positive effect on economic growth in non-democratic regimes, rather than in democratic regimes	(Libman 2013)	2000-2006	Russia, 72 Russian regions	Panel, OLS, Fixed Effect and Two-Way FE	Oil and gas extraction relative to gross regional product (GRP): the extraction value is calclated by multiplying the quantity of oil and gas extracted (in tons and cubic meters, respectively) by the average annual export prices for crude oil and natural gas.
12	Mining has a positive impact on non-mining employment and family income	(Fleming, Measham, and Paredes 2015)	2001-2011	Australia, 449 non-metropolitan local government areas (LGAs)	OLS	Independent variable is mining employment whics is the (log) change in mining employment in region I between 2001 and 2011. Dependent variable is using two proxies which are non-mining employment growth and income

No	Findings (+)	Authors	Period	Sample	Techniques	Definition of resources
						growth model, where median family income is used
13	Coal based employment is negatively correlated with the percent change in per capita during 1990-2000, when coal prices were low, and positively correlated during 2000-2010, when coal prices were higher. A similar effect was found for oil and gas employment.	(Betz et al. 2015)	1990-2000, 2000-2010	Continental U.S. counties and specifically within the Appalachian Regional Commission (ARC)	Cross-section regression	Initial mining industry employment shares consists of coal, oil, and natural gas, and other mining sectors.
15	Boom countries in gas production have higher has positive impact on growth in total employment, wage and salary income and median household income	(Weber 2012)	Change between period 1998/99 – 2007/08	209 counties in Colorado, Texas and Wyoming		A Boom county is defined as a county in the top 20% for its upward change in gas production
16	Mining operations and fiscal revenues positively affect social and economic development (as measured by annual growth rate in GDP, direct employment in mining, and in indirect employment,	(Mcmahon and Moreira 2014)	2001-2010	Chile, Ghana, Indonesia, Peru and South Africa (had long mining histories)	Case studies	South Africa and Chile (had a large mining in the 1980’s),

Appendix 6: Panel data regression (year by year) results using Pooled OLS

VARIABLES	(1) OLS1	(2) OLS2	(3) OLS3	(4) OLS4
Mining Dependence	1.385***			
	(0.0616)			
Mining Revenue		2.529***		
		(0.0873)		
Oil&gas revenue			2.610***	
			(0.0994)	
Coal Revenue				4.604***
				(0.280)
Population (in logs)	-0.159***	-0.123***	-0.143***	-0.129***
	(0.0104)	(0.00994)	(0.0102)	(0.0105)
Labor force participation rate	-0.209**	0.0945	0.215**	-0.386***
	(0.0871)	(0.0871)	(0.0909)	(0.0991)
Household elect.	1.387***	1.332***	1.384***	1.365***
	(0.0449)	(0.0442)	(0.0441)	(0.0477)
Constant	3.875***	3.506***	3.538***	3.890***
	(0.0858)	(0.0862)	(0.0896)	(0.0937)
Observations	4,290	4,290	4,290	4,290
R-squared	0.277	0.347	0.306	0.232