UNIVERSITY OF SUSSEX

Three Essays on

Growth and Economic Diversification

in Resource-rich Countries

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Statement: I hereby declare that this thesis has not been and will not be submitted in whole or in part to another University for the award of any other degree.

Nouf Alsharif

THREE ESSAYS ON GROWTH AND ECONOMIC DIVERSIFICATION IN RESOURCE-RICH COUNTRIES

SUMMARY

This thesis looks into the relationship between natural resources and non-resource economic activity in resource-rich countries. This relationship has been investigated through the literature of the "resource curse" which was first noted by Sachs and Warner (1995) who show a significant negative relation between natural resource dependence and income growth. Despite the developing literature in that area, empirical tests suffered from endogeneity. In this thesis, I try to add more resilient identification strategies in order to assess the effect of resource abundance on the macro economy using exogenous variations in 136 countries from 1962-2012.

The first essay of this thesis examines the correlation between natural resource rents and economic diversification. The main question I ask in this essay is can resource-rich countries diversify their economies? To address this issue, the essay empirically tests diversification in exports, in employment and in value added and finds a significant negative impact.

In the second empirical essay of this thesis, I focus on giant oil and gas discoveries as the main external variation and test the role of institutional quality in diversification when a country becomes resource abundant. Results show that all countries with varied institutional quality go through export concentration after giant oil discoveries.

The third empirical essay looks more thoroughly into the manufacturing sector. I estimate the causal effect of two commodity shocks suggested by the Dutch Disease hypothesis on the tradable manufacturing industries: giant oil discoveries as a resource discovery shock, and oil price boom and bust as a commodity price shock. The results suggest a negative impact on the tradable industries growth in manufacturing value added and wages. These results add more credible empirical evidence to the Dutch Disease literature.

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Chapter 1

Introduction

The literature on the relationship between natural resources and non-resource economic activity focuses on the concept of the "Dutch Disease," while the "resource curse" was first noted by Sachs and Warner (1995), who show a significant negative relation between natural resource dependence and growth in GDP per capita. Despite the developing literature in that area, empirical tests suffer from endogeneity. Many papers in the literature have used the share of natural resources in GDP or in exports as a resource variation, whereby this variable could be reversely affected by the country's growth and development. In this thesis, I try to add more resilient identification strategies in order to assess the effect of resource abundance on the macroeconomy using exogenous variations.

The first two empirical chapters of this thesis I study the relationship between natural resources and economic diversification. Through the development literature, a number of studies have investigated the relationship between diversification and development. The findings vary across papers depending on the methodological approach used, the data set, and the diversification measures (De Benedictis et al., 2009). Cadot et al. (2011) argue that diversification should not be taken as a policy objective for two reasons: first, they emphasise the importance of specialisation, not diversification, following Ricardian theories that stress the importance of specialisation, not diversification. Second, they argue that by looking into exports, the Heckscher-Ohlin model implies that export patterns are largely determined by endowments, drawing attention to factor accumulation, not diversification.

However, policymakers in developing countries and resource-rich countries are constantly preoccupied by diversification, as they believe it is the path towards higher development, according to Papageorgiou and Spatafora (2012). Gylfason (2011) argues that economic diversification could stimulate growth by attracting new economic activity that avoids excessive reliance on primary production in a few natural-resource based industries, thus facilitating the transfer of labour from low-paying jobs in low-skill, intensive farming and agriculture to more lucrative jobs in more high-skill, intensive occupations in manufacturing. Gylfason (2011) also argues that depending on natural resources could be good for growth, if well managed and used to diversify the economy. In exports, diversification may help countries to upgrade their resource-based sectors, as they move away from unprocessed primary exports, to more complex products and services (Gelb & Grasmann, 2010). A higher resource dependency makes diversification more difficult, but resource-rich countries still want to diversify for a number of reasons (Gelb & Grasmann, 2010). First, export diversification is associated with higher long-run growth, as engaging in manufacturing enables dynamic learning-by-doing that raises productivity and income. Second, diversification exposes producers to a wider range of information about foreign markets and may open the way to other sectors. Third, diversification reduces the impact of volatile resource prices.

The first empirical chapter of this thesis examines the correlation between natural resource rents and the economic diversification. The main question I ask in this paper is: can resource-rich countries diversify their economies? To address this issue, the essay empirically tests diversification in exports, in employment and in value added in 136 countries from 1962-2012. In this paper, I follow Imbs and Wacziarg (2003) in tracking the noted U-shaped diversification path along development, but I find that this shape actually flattens when resource rents get higher. Intuitively, the more the resource rents the country receives, the less likely it would go through any diversification as it develops. Alternatively, more concentration in nontradable sectors increases. I combine data on a number of resource rents to address any heterogeneity that could arise in different resources. The concern with this analysis is that there may be confounding variables where diversification could reversely affect resource rents. To tackle this issue, I instrument for resource rents by using international commodity prices which are directly related to the resource revenues but not directly to diversification measures per se. The identification strategy argues that commodity prices are exogenous, as they are mainly driven by international supply and demand. Another factor in that paper is the different diversification outcomes across different kinds of resources. I suggest that oil and gas rents have a significant impact on export concentration, whereas other renewable resources tend to increase export diversification and employment.

Between different country groups, there is a significant positive impact of natural resources on diversification among developed countries, while developing countries tend to develop more concentrated in exports, employment and value added. In the second empirical chapter of this thesis, I extend this analysis and focus on oil and gas as the main commodity. I also test the role of institutional quality on diversification when a country becomes resource abundant, driven by the heterogeneous outcomes I find between developed and developing countries in the first chapter. To measure the natural resources, I use giant oil discoveries as a news shock on economic diversification, using panel analysis and fixed effects model. Institutional quality measures used in this chapter are Polity2 and executive constraints. The results are largely similar between the two measures. I further tackle any endogeneity concerns that could arise from using the giant oil discoveries as an exogenous variable by using oil reserves and natural disaster as instruments for oil discoveries following Cotet and Tsui (2013). The results suggest that the combination of grabber-friendly institutions and giant oil discoveries leads to a less diversified economy in non-tradable sectors, whereas producer-friendly institutions help countries to take full advantage of these discoveries and their following revenues, and maintain the employment share in the manufacturing sector and tradables. However, I find little evidence that producer-friendly institutions help countries to avoid export concentration: all countries tend to have concentrated exports with large shares in the resource sector.

In addition, the second chapter's results indicate that the manufacturing sector is the most negatively affected sector. More labour movement out of the tradable sector could have a negative impact on growth in the long run, which might be a single step towards the spending effect of the Dutch Disease. It is possible that the final impact would take a longer time to stabilise than is studied here. These results and the standing question about the impact on the manufacturing sector are the key to the third chapter's question, where I ask: what happens within the manufacturing sector and which industries are mainly affected by the resource abundance?

The third empirical chapter looks more thoroughly into the manufacturing sector and the heterogeneity between its industries as a response to the resource booms. In this chapter, I estimate the causal effect of two commodity shocks suggested by the Dutch Disease hypothesis on the tradable manufacturing sector: giant oil discoveries as a resource discovery shock, and oil price boom and bust as a commodity price shock. Using panel analysis, I compare between countries that have discovered giant oilfields and countries that have not during 1962-2012. I also observe the outcomes during the oil booms and busts. The methodology is adapted from Rajan and Subramanian (2011), which evaluates the impact of receiving foreign aid on the tradable manufacturing sector. I follow Rajan and Subramanian (2011) in using the dataset provided by the United Nations Industrial Development Organisation (UNIDO): the industrial statistics database, which is derived largely from industrial surveys. I also follow their exportability classification in assigning certain manufacturing industries as “exportable” and focusing on them to assess the impact on the tradable industries within the manufacturing sector. Recent literature on the Dutch Disease indicates a positive impact of oil booms on manufacturing. I suggest that it is true that total manufacturing could benefit from oil shocks, through increased local demand for manufactured goods resulting from the revenue windfall that was met by increased demand on imports and local production. However, the main suggestion of this chapter is that tradable industries in manufacturing are harmed by the oil shocks.

The rest of this thesis is structured as follows. Chapter 2 examines if resource rents have any impact on economic diversification along the development path. Chapter 3 examines if institutional quality in oil countries could have any role in determining the impact of oil shocks on economic diversification. Chapter 4 examines the Dutch Disease mechanism thoroughly by looking into the heterogeneity between manufacturing industries. Chapter 5 summarises the findings of this thesis and discusses the limitations of this work, and it provides potential suggestions for further research.

Chapter 2

Natural Resources and Diversification

2.1 Introduction

Natural resource rents exceed $4 trillion per year, amounting to 7 percent of world GDP. Non-renewable resource revenues are a dominant feature of 50 economies with a combined population of 1.4 billion people. There are 24 countries for which resources make up more than three quarters of their exports, 13 countries for which resources make up at least 40 percent of their GDP, and 18 countries in which resources provide more than half of fiscal revenue.[1]

Resource-rich countries have been historically heavily dependent on a limited range of natural resources, mostly for export. This limited diversification may lead to unsustainable growth, driven by a high concentration in low productivity sectors. Concentration in such sectors may lead to high vulnerability to macroeconomic instability, price volatility and external shocks. Many resource-rich countries aspire to a diversified economy, but many of them – especially the less developed countries – have limited experience with regard to which aspects of diversification are important.

[1] (IMF 2007) and van der Ploeg and Venables (2012)

In this paper, we test the impact of natural resource rents on diversification in exports, in employment and in value added. By using employment data, Imbs and Wacziarg (2003) find that diversification path follows a U-shaped pattern in relation to per capita income: countries tend to diversify at early stages of development, and then at higher stages of income they tend to specialise in certain sectors. This paper revisits the issue using an additional perspective: we investigate the effect of resource rents on the noted U-shaped diversification pattern in employment, in addition to value added and exports. We find a significant negative relationship between resource rents and diversification.

The literature on the relationship between resource rents and non-resource economic activity focuses on the concept of the "Dutch Disease," which is a widely-used term in the development literature. The Economist magazine coined the term in 1977 to explain the gas boom implications on the Dutch economy.

The extensive literature on the Dutch disease is pioneered by Corden and Neary (1982), who show a decline in manufacturing employment and exports as a result of resource boom. Three factors can cause this boom: a technology-induced rise in productivity, a new resource discovery, or a rise in the commodity world price. They distinguish between two main effects of the resource boom on the manufacturing sector. Firstly, the *spending effect* occurs when a sudden rise in the value of the natural resource exports raises real income leading to extra spending on services, which raises prices and leads to adjustments in real exchange rate. That makes exporting non-resource commodities more difficult, and makes competing with imports across a wide range of commodities harder. Foreign exchange earned from the resource exports may be used to purchase internationally traded goods, at the expense of domestic manufacturers of the goods. Secondly, domestic resources such as labour and materials shift to the resource sector, where the *resource movement effect* takes place. Consequently, the price of these resources rises on the domestic market, thereby increasing the costs to producers in other sectors. Eventually, extraction of natural resources sets in motion a dynamic that gives primacy to two domestic sectors – the natural resource sector and the non-tradable sector, at the expense of more traditional exports sector[2].

Arezki and Ismail (2010) test the Dutch disease on a sample of 32 oil-rich countries from 1992 to 2009 and find that during an oil boom, fiscal policies have helped to reduce capital expenditure. Harding and Venables (2016) find that exports of natural resources crowd out non-resource exports. They find that in countries with high income and good governance, the impact on non-resource exports becomes greater, as these countries tend to have higher manufacturing in their non-resource exports.

The "resource curse" was first noted by Sachs and Warner (1995, 2001), who show a significant negative relation between natural resource dependence and growth in GDP per capita. They also argue that resource abundance squeezes the manufacturing sector, as in the Dutch disease model. Other studies considered oil rents specifically. Ross (2001) and Sala-i-Martin and Subramanian (2003) find a negative relation between oil rents and economic performance. Other papers show that the impact of resource abundance is mainly driven by political factors (Tornell & Lane, 1999).

We also test if different kinds of resources could have varied impacts on diversification, as Bhattacharyya and Collier (2014) show that resource curse occurs in the case of point resource natural resources such as minerals, but not in renewable point source resources such as agriculture and forestry.

To date, there are not many empirical studies on diversification. A few exceptions include Imbs and Wacziarg (2003), who find that employment diversification follows a

[2] For more details, see Humphreys, Sachs and Stiglitz, ***Escaping the Resource Curse*** (Columbia University Press, 2007) and van der Ploeg and Venables (2012).

U-shaped pattern in relation to per capita income: countries tend to diversify at early stages of development, and then at higher stages of income they tend to specialise in certain sectors. Koren and Tenreyro (2007) also find the U-shaped pattern in plotting production concentration against income, but the depth of that shape varies across different income groups. Moore and Walkes (2010) find a positive relationship between economic volatility and concentration. In studying trade diversification, a number of papers find that exports are more concentrated than production, such as Hausmann and Rodrik (2003) and Easterly et al. (2009). Cadot et al. (2011) find the U-shaped pattern in export diversification, as countries tend to reconcentrate in exports after a certain point of income.

Investigating productivity growth and structural change, McMillan and Rodrik (2011) argue that in developing countries, there are large productivity gaps between different parts of their economies, and between different firms within the same part or industry. These gaps are smaller in developed countries. They acknowledge that structural change could move in different directions along with the economic development process. In resource-rich countries particularly, natural resources do not generate much employment compared to manufacturing and other tradable sectors, which takes structural change in a direction away from productive sectors.

This paper adds to the literature through examining the effect of resource rents on diversification. As shown above, previous literature covered the effect of development on diversification, or studied the effect of natural resources on development. In this paper, we combine the two strands of literature and study the effects of resource rents on structural change in employment and value added (internal diversification), and the effect on exports (external diversification). We examine the concentration in employment and exports in resource and non-resource, tradable and non-tradable sectors. Previous literature examined these effects separately – either structural change or exports – and to our knowledge, none of them examined the effect of natural resources directly on diversification.

The rest of the paper continues as follows: section 2 briefly describes economic diversification; section 3 defines the data and outlines the methods; section 4 presents the empirical results; and section 5 concludes.

2.2 Diversification: How and why

Through the development literature, a number of studies have investigated the relationship between diversification and development. The findings vary across papers depending on the methodological approach used, the data set, and the diversification measures (De Benedictis et al., 2009). Some of these studies find a monotonic relationship between diversification and development, where countries tend to diversify moving along the development path (Stokey, 1988), while other studies find countries grow into more specialisation as they develop (Krugman, 1987).

More recently, a growing number of empirical studies have investigated the relationship between diversification and development. The highly cited paper by Imbs and Wacziarg (2003) finds a nonmonotonic relationship, where diversification takes a U-shape pattern, a result found by other following papers such as Koren and Tenreyro (2007) and Cadot et al. (2011). Cadot et al. (2011) argue that diversification should not be taken as a policy objective for two reasons: first, they emphasise the importance of specialisation, not diversification, following Ricardian theories that stress the importance of specialisation, not diversification. Second, they argue that by looking into exports, the

Heckscher-Ohlin model implies that export patterns are largely determined by endowments, drawing attention to factor accumulation, not diversification.

However, policymakers in developing countries and resource-rich countries are constantly preoccupied by diversification, as they believe it is the path towards higher development, according to Papageorgiou and Spatafora (2012). Alsharif et al (2017) revisits the literature on diversification in resource rich countries, and shows trends in non-oil exports and non-oil private sector employment. Gylfason (2011) argues that economic diversification could stimulate growth by attracting new economic activity that avoids excessive reliance on primary production in a few natural-resource based industries, thus facilitating the transfer of labour from low-paying jobs in low-skill, intensive farming and agriculture to more lucrative jobs in more high-skill, intensive occupations in manufacturing. Gylfason (2011) also argues that depending on natural resources could be good for growth, if well managed and used to diversify the economy. In exports, diversification may help countries to upgrade their resource-based sectors, as they move away from unprocessed primary exports, to more complex products and services (Gelb & Grasmann, 2010). A higher resource dependency makes diversification more difficult, but resource-rich countries still want to diversify for a number of reasons (Gelb & Grasmann, 2010). First, export diversification is associated with higher long-run growth, as engaging in manufacturing enables dynamic learning-by-doing that raises productivity and income. Second, diversification exposes producers to a wider range of information about foreign markets and may open the way to other sectors. Third, diversification reduces the impact of volatile resource prices. Van der Ploeg and Venables (2012) argue that to achieve diversification in resource-rich economies, public and private investments are needed to work jointly through investments in human and private capital.

Figure 2-1.A shows the difference in export diversification between developed and developing countries in the sample. It shows developing countries increased their export diversification during the sample period more rapidly than developed countries. Gelb and Grasmann (2010) note that developing countries in general have had successfully diversified their economies and exports. They note that in the 1960s, about 80 percent of developing countries' exports were primary commodities, while recent figures show that almost 80 percent are industrial products (although some primary industries are classified as industrial). These figures relate to the U-shaped pattern found by Imbs and Wacziarg (2003), assuming that developing countries are in the initial stage, where concentration is still high.

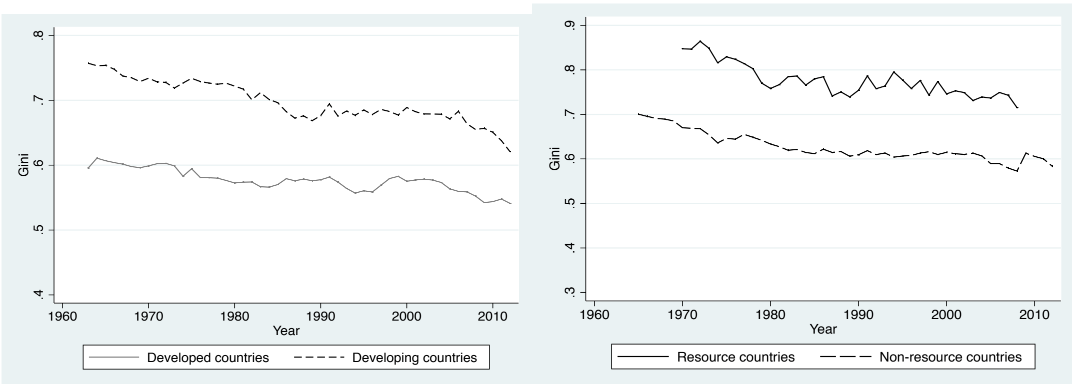
Figure 2-1.B shows the difference in exports diversification between resource and non-resource countries in the sample. What is apparent is we can see the higher level of concentration in the resource countries exports, which is mainly driven by resources.

Elbadawi and Gelb (2010) show two types of diversification: diversifying by introducing new sectors in the economy, and diversifying within the resource sector. We focus on the first type in this paper. Diversification strategies do not always succeed. Esanov (2012) lists certain criteria for successful outcomes: sound macroeconomic environment, designing a realistic strategy taking into consideration local factors, well-functioning government institutions, adequate financial sector and social infrastructure to support diversification efforts, and creating special incentives to facilitate export diversification.

Rodrik (2007) emphasises the new findings by Imbs and Wacziarg (2003), and finds it very interesting that it goes against the standard beliefs associated with the principle of comparative advantage. Rodrik (2007) suggests acquiring mastery over broader range of activities, instead of concentrating on one specialization. He argues that the main key to diversification is direct government intervention or any other public action. He mainly stresses three keys to successful diversification strategy: first, public-private collaboration; second, "self-discovery" of which new activities can be produced at low enough cost to be profitable; and third, discovering that certain goods, already well established in world markets, can be produced locally at low cost.

Figure 2-1: Export diversification

A. Developed and developing countries **B. Resource and non-resource countries:**



Notes: Gini ranges between 0 and 1; lower Gini indicates higher diversification. Source: WITS (2013)

2.3 Data and empirical strategy

2.3.1 Measures of economic diversification

The dataset in this study includes sectoral data on structural change measured by employment, value added and exports. The number of countries in the dataset is 136, ranging between all levels of development. The data are annual, covering the period from 1962 to 2012. There are many measures for sectoral diversification; most of them are borrowed from the income equality literature. Here we calculate six measures of diversity, but we report only three measures: the Gini, Theil and Herfindahl-Hirschman indices. Table A-2 in the appendices presents descriptive statistics of these measures, and Table A-3 in the appendices presents the correlation between all the measures, which is rather high. Imbs and Wacziarg (2003) use Gini, HHI and the Coefficient of Variation. Cadot et al. (2011) use Gini and HHI and Moore and Walkes (2010) use only HHI. Lederman and Maloney (2003) use HHI. McMillan and Rodrik (2011) use the Coefficient of Variation. All measures are calculated in this study, but we report the Gini index only due to the high correlation between the three measures. (See appendix A for full data description.)

We calculate diversity for all sectors first, and then for all non-resource sectors. To get the non-resource sector values in the ILO data, we exclude "Mining and Quarrying," and in the WITS exports data we exclude "Crude material, inedible, except fuels," "Mineral Fuels, lubricants and related materials" and "Commodities not classified according to kind." The UNIDO data does not cover resource sectors at all.

From Table A-2 in the appendices we can take that highest diversification in employment (using ILO dataset) happened in Algeria, in 1984. The highest export diversification (using WITS dataset) happened in Greece, 2006, while the highest concentration in exports happened in Libya between 1976 and 1981, dominated by the mineral exports sector[3].

Employment data

Sectoral employment data are from International Labour Office (ILO, 2013) and United Nations Industrial Development Organisation (UNIDO, 2012). ILO data covers 127 countries, while UNIDO covers 125 countries. The ILO data includes all economic activities at the 1-digit level between 1969 and 2008. Sectoral shares are in percentages.

[3] Due to data limitations, not all specifications cover exactly 136 countries and in most specifications, the panel is unbalanced. Appendix A presents a list of countries included in the sample of each specification. The size of the sample in this chapter is mainly dependent on the size of the resource rents dataset.

The unbalanced panel has 2369 observations (country-year). The ILO dataset reports employment in different classifications: some countries use the ISIC-revision 2, others moved to ISIC-revisions 3 and 4 in recent years, and some are using their own national classification. Employment data in the more disaggregated ISICrev3 and ISICrev4 were aggregated to ISICrev2, following Imbs and Wacziarg (2003), Timmer and Vries (2007) and McMillan and Rodrik (2011). If a country reports two revisions, the older one is used. For example, if a country reports revision 2 and 3 for the same year revision 2 is chosen, and if it reports revision 3 and 4 for the same year revision 3 is chosen. Moreover, if a country reports labor survey and official estimates for the same period, I choose the source that is mostly used to get harmonized numbers, otherwise the labor survey is chosen to have better credibility. Regarding the national surveys data, years that report classifications not matching revision 2 are dropped, as the data will get misleading. In more details; the segregated sectors in revision 3 mostly have the same title as they did in the reported aggregated sector in revision 2, and official estimates are preferred over labour surveys. Data not following ISIC conventions are dropped. Table A-1 in the appendices shows the concordance between ISICrev3 and ISICrev2.

ILO data sometimes have inconsistent observations reported in certain sectors or years, as countries sometimes change their calculation method, even if they still use the same classification/revision. This is part of the data cleaning taken into consideration in this study, by dropping the inconsistent observations, making the panel more harmonised. For example, observations for Guatemala are dropped for the years 1990 and 1991. The data is reported using the same classification (ISIC-Rev.2) but the total number of the labour force was 2.136 (million) in 1981, and 2.228 in 1982, and 2.644 in 1987, and 2.840 in 1989, and then suddenly dropped to 650.4 (thousands) in 1990 and 681.4 in

1991, and jumped back again to 5.390 in 2006 to be consistent with the previous sequence.

Our alternative data source is UNIDO, which covers manufacturing activities only at the 3-digit level of disaggregation (the main 23 industrial sectors) between 1963 and 2010 (INDSTAT2). (INDSTAT4 disaggregates to 4-digit level but only goes back to 1985.) The UNIDO dataset is consistent over the years and did not need adjustment. The unbalanced panel has 3564 employment observations (country-year).

Value added and labour productivity

The UNIDO dataset also provides information on value added per sector, offering an additional measure of sector size and productivity in industrial employment. The value added dataset covers almost the same period as the employment dataset, although some countries do not report the two sets equally. The unbalanced panel has 3465 added-value observations (country-year).

Exports data

Exports data are from the World Integrated Trade Solution (WITS), which is a collaboration between the World Bank and the United Nations Conference of Trade and Development (UNCTAD). The export data covers 133 countries. Data is selected in SITC-1-digit aggregation containing the main 10 trade sectors. Values are reported in constant 1000 USD with the base year being 2000. The unbalanced panel has 4575 observations (country-year). The WITS data values are consistent over the years and did not need any adjustment.

2.3.2 Empirical strategy

The methodology has three steps. First, we use panel data to examine the relationship between resource rents and diversification. Second, we use commodity prices as an instrumental variable for resource rents. Third, we test the heterogeneity of natural resources in different specifications.

To estimate the effect of resource rents on diversification, we use the following model based on Imbs and Wacziarg (2003):

$$Div_{it} = \alpha_i + \beta_t + \gamma RR_{it} + \phi X_{it} + \varepsilon_{it} \tag{2-1}$$

where Div_{it} is the diversification measure in employment, value added and exports; α_i are the country fixed effects, β_t are the year fixed effects; RR_{it} is the resource rent measure, which is the resource rent per capita; X_{it} is a group of control variables, including GDP per capita and GDP per capita squared; ε_{it} is the error term. The parameter of interest is γ, which shows the effect of RR_{it} on Div_{it}.

There is a possibility of endogeneity in equation 2-1. Particularly, there may be confounding variables where diversification could reversely affect resource rents. To tackle this issue, we instrument for resource rents by using international commodity prices provided by Burke and Leigh (2010), which is a weighted index of 50 commodity prices covering the years 1950-2010. Commodity prices are directly related to the resource rents, but not directly to diversification measures per se, as diversification covariates in this analysis is a calculated figure that shows diversity between different sectors in the economy – exports and employment – using the inequality measures: Gini, Theil and HHI among others. This figure does not represent GDP or income or any other share in the macro economy that could be affected by the international index of commodity prices. Our identifying strategy is that commodity prices are exogenous, as they are mainly driven by international supply and demand. Therefore it is a valid instrument for resource rents (Bhattacharyya & Collier, 2011). In addition, Burke and Leigh (2010) argue that since countries are usually price-takers for their commodity exports, world price index variations are exogenous in most instances (Deaton & Miller, 1995). F-statistics and critical values reported in the results show the validity of the chosen instrument. All regressions use robust standard errors to account for heteroskedasticity.

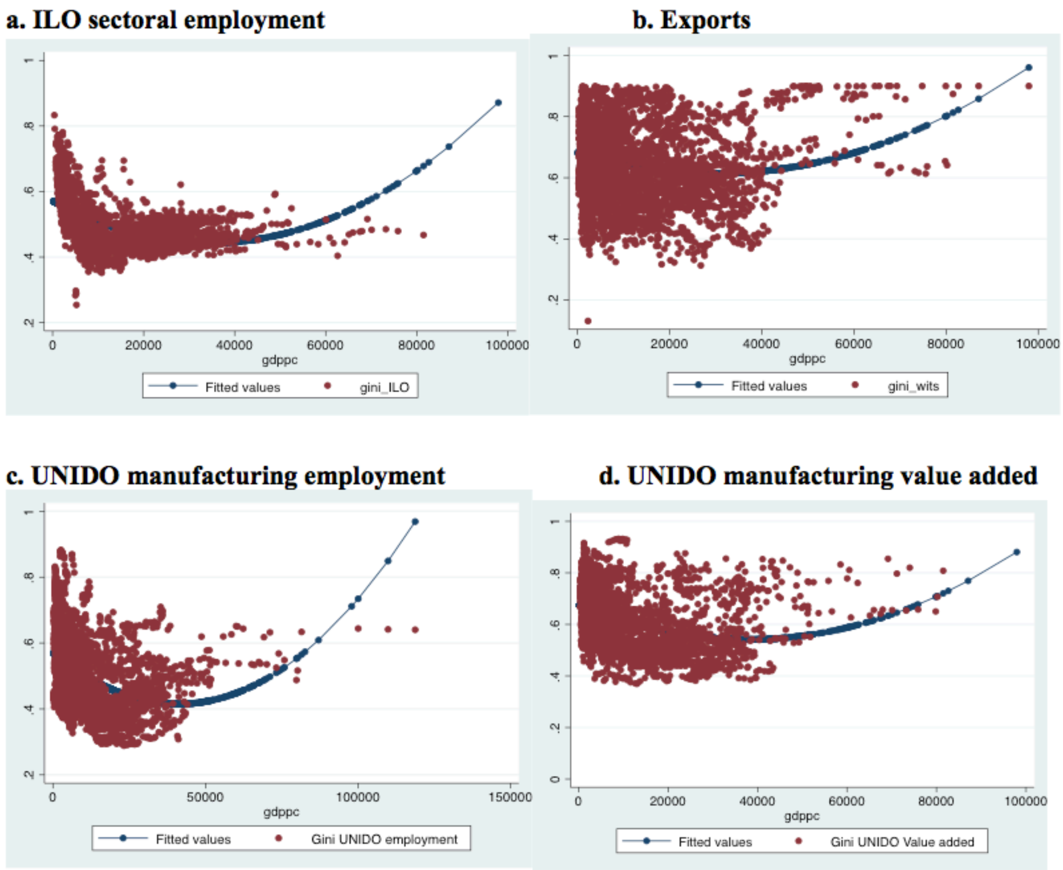
The employment data are from the International Labour Office (ILO, 2013) for nine main sectors (1-digit level) covering the years 1969-2009, and the United Nations Industrial Development Organisation (UNIDO, 2012) for 23 main sectors (3-digit level, INDSTAT2) covering the years 1963-2010. Note that UNIDO data are partial, covering only manufacturing employment and value added. It is included here because the value added data shine an additional light on diversification and structural change. Exports data are from WITS for the ten main sectors (1-digit level), covering the years 1962-2012. Income data are from Penn World Tables (PWT) version 8.0, which goes back to 1950.

2.4 Results

2.4.1 Natural resources and diversification

We begin by revisiting the nonmonotone relationship between diversification and development uncovered by Imbs and Wacziarg (2003) and Cadot et al. (2011). Figure 2-2 shows the existence of the nonmonotonic U-shape path in our data in employment, value added and exports. Column 1 in results Tables 2-1, 2-2 and 2-3 shows the highly significant coefficients, where the U-shape persists in diversification through all specifications even after counting for the non-resource sectors only.

Figure 2-2: Revisiting the U-shape development path noted by Imbs and Wacziarg (2003) and Cadot et al. (2011) in :



Notes: the U-shaped pattern based on our data. Countries diversify first and then specialise again through all data groups. Data sources: (ILO, 2012), (WITS, 2013) and (UNIDO, 2012)

Secondly, we examine the effect of the natural resource rents on sectoral employment to test the structural change movements in resource countries. Table 2-1 shows the results of estimating equation 2-1 with diversification in the ILO data as the dependent variable. Each column separates the effects between the whole sample and only non-resource sectors. Across different specifications, the coefficients are mostly positive and significant (+ coefficient is concentration, - coefficient is diversification). Column 5 shows the IV estimation results; there is a large and significant negative effect of the resource rents on ILO sectoral employment diversification. Coefficients are larger within the non-resource sectors, showing that employment concentration happens out of the resource sector, which is usually capital intensive and does not create many jobs.

Dutch disease theory predicts that a resource boom increases wages in the booming sector, and thus increases employment in that sector affected by the spending effect. However, due to the fact that the resource sector is capital intensive, employment concentration occurs in other non-tradable sectors affected by the resource movement effect.

Within the UNIDO manufacturing data, we test the effect on manufacturing employment and value added. Table 2-2 shows that there is a significant negative effect of the resource rents on manufacturing employment, and on the manufacturing value added. This could reflect increased local demand on manufactured goods as an implication of the Dutch disease spending effect. This result might be also affected by low employment in the resource sector as explained previously.

We next turn from employment to exports, to test the effect of resource rents on the tradable sectors. The Dutch disease model predicts a decline in producing tradable goods, and higher exports of the natural resources. Table 2-3 shows that there is a significant negative effect of the resource rents on export diversification, in both full sample exports and in non-resource sectors. Concentration in resource exports examined by the total exports (All) is larger in most specifications. Less manufacturing output and other tradable goods could cause the noted higher diversification in non-resource sectors, as the Dutch disease model predicts.

Table 2-1: Dependent variable: Diversification in sectoral employment (Gini)

	(1) OLS - Imbs & Wacziarg		(2) OLS-linear		(3) OLS-linear		(4) OLS-nonlinear		(5) FE		(6) IV	
	All	NR	All	NR	All	NR	All	NR	All	NR	All	NR
Resource Rent per capita			-0.002	0.000	0.007***	0.010***	-0.008***	-0.006**	0.001	0.002	0.035***	0.041***
			(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.003)	(0.001)	(0.001)	(0.009)	(0.010)
GDPpc	-6.4e+03***	-7.7e+03***			-2.9e+03***	-3.5e+03***	-7.2e+03***	-8.3e+03***	2557.321***	2005.802**	8284.188***	8499.629***
	(678.072)	(747.716)			(142.870)	(159.629)	(649.670)	(721.390)	(809.990)	(961.507)	(1840.290)	(2067.742)
$GDPpc^2$	8.7e+07***	1.1e+08***					1.1e+08***	1.3e+08***	3.6e+06	1.2e+07	-1.2e+08***	-1.3e+08***
	(1.8e+07)	(2.0e+07)					(1.7e+07)	(1.9e+07)	(1.3e+07)	(1.6e+07)	(3.7e+07)	(4.1e+07)
Country & year dummies	No	No	No	No	No	No	No	No	Yes	Yes	Yes	Yes
Kleibergen-Paap Wald F-stat											147.849	146.86
Stock-Yogo critical value											16.38/ 5.53	16.38/ 5.53
Observations	2169	2169	2169	2169	2169	2169	2169	2169	2169	2169	2167	2167
R^2	0.253	0.289	0.001	0.000	0.162	0.192	0.266	0.294	0.843	0.845	0.730	0.730

Table 2-2: Dependent variable: Diversification in UNIDO Industrial Employment (Gini)

	(1) OLS - Imbs & Wacziarg		(2) OLS-linear		(3) OLS-linear		(4) OLS-nonlinear		(5) FE		(6) IV	
	EMP	VA	EMP	VA	EMP	VA	EMP	VA	EMP	VA	EMP	VA
Resource Rent per capita			0.003***	0.008***	0.005***	0.010***	0.013***	0.018***	0.001*	0.002***	0.011***	0.009**
			(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.004)	(0.004)
GDPpc	-2.9e+03***	-2.4e+03***			-770.631**	-603.213	-4.0e+03***	-3.8e+03***	1032.003***	-267.128	291.756	-794.572**
	(255.278)	(297.548)			(365.371)	(379.116)	(270.244)	(303.873)	(201.739)	(188.237)	(341.811)	(368.740)
$GDPpc^2$	5.3e+06***	4.8e+06***					7.0e+06***	7.2e+06***	-1.3e+06***	6.2e+05**	8.8e+04	1.6e+06**
	(5.1e+05)	(5.4e+05)					(5.4e+05)	(5.6e+05)	(3.1e+05)	(3.1e+05)	(6.1e+05)	(6.6e+05)
Country & year dummies	No	No	No	No	No	No	No	No	Yes	Yes	Yes	Yes
Kleibergen-Paap Wald F-stat											21.716	20.48
Stock-Yogo critical value											16.38/5.53	16.38/5.53
Observations	3304	3269	3304	3269	3304	3269	3304	3269	3304	3269	3304	3269
R^2	0.094	0.063	0.002	0.021	0.026	0.035	0.141	0.145	0.859	0.839	0.844	0.832

Table 2-3: Dependent variable: Diversification in WITS exports (Gini)

	(1) OLS - Imbs & Wacziarg		(2) OLS-linear		(3) OLS-linear		(4) OLS-nonlinear		(5) FE		(6) IV	
	All	NR	All	NR	All	NR	All	NR	All	NR	All	NR
Resource Rent per capita			0.016***	0.004***	0.016***	0.006***	0.020***	0.010***	0.003***	-0.000	0.033***	0.053***
			(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.009)	(0.014)
GDPpc	-4547.8***	-5260.8***			-59.510	-463.631***	-1.4e+03***	-1.9e+03***	1141.262***	206.356	326.509	-1.2e+03
	(-7.32)	(-9.95)			(138.453)	(152.077)	(253.877)	(257.326)	(173.109)	(409.862)	(374.642)	(798.129)
$GDPpc^2$	7.5e+07***	7.5e+07***					3.4e+06***	3.5e+06***	-1.9e+06***	-7.7e+05	2.9e+05	3.0e+06**
	(5.38)	(6.55)					(5.6e+05)	(5.5e+05)	(3.2e+05)	(6.8e+05)	(7.5e+05)	(1.5e+06)
Country & year dummies	No	No	No	No	No	No	No	No	Yes	Yes	Yes	Yes
Kleibergen-Paap Wald F-stat											24.147	24.072
Stock-Yogo critical value											16.38/5.53	16.38/5.53
Observations	4216	4036	4228	4047	4227	4046	4227	4046	4227	4046	4221	4040
R^2	0.055	0.073	0.074	0.005	0.074	0.012	0.095	0.035	0.765	0.655	0.665	0.313

Notes: Standard errors in parentheses, All:All sectors, NR:Non-resource sectors. +Coefficient shows concentration, -coefficient shows diversification. (6) uses instrumental variable "commodity prices". All variables are divided by one billion to get shorter and easier to read results. *Data sources*: Employment data from ILO (2013); Commodity price index is from Burke and Leigh (2014) a weighted index for 50 commodities; Resource rent per capita is calculated using resource rents data from the World Bank and population data from Penn World Tables PWT 8.0; GDPpc data is obtained from PWT 8.0,*p<0.10,**p<0.05,***p<0.01.

In all three tables (2-1), (2-2) and (2-3), the magnitude of the IV estima is larger than those of the fixed effects in column 5, and than those column 4 (only in tables 2-1 and 2-3). This could be explained that the I the local average treatment effect (LATE), where the OLS is estimati treatment effect (ATE) over the entire population. Therefore, the IV esti larger than OLS estimates because of heterogeneity in resource re resource countries studied in the sample.

Table 2-4 reports the first stage regression, where commodity price i highly significantly correlated with resource rents. As we discussed ear it is not a weak instrument as it satisfies the Stock-Yogo criteria (see tab 2-3).

Table 2-4: Resource rents and diversification: First stage regressions

	(1) Resource rents per capita	(2) Resource rents pe
Commodity Price	1.85e-06*** (4.62)	1.26e-06** (3.58)
Controls	No	Country & year du
Observations	8057	8057
R^2	0.006	0.559

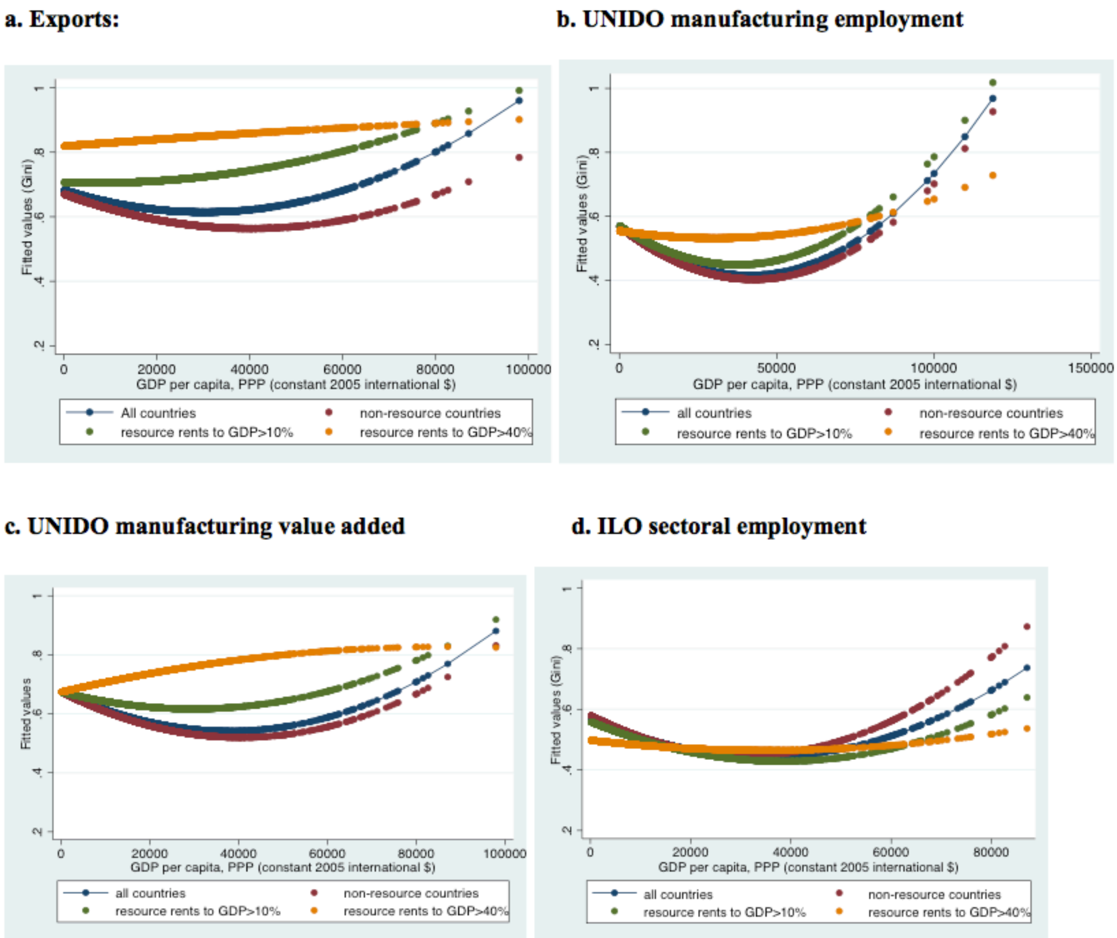
Notes: Robust standard errors are in parentheses.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, Data s price index is from Burke and Leigh (2014) a weighted index for 50 commodities; Resourc calculated using resource rents data from the World Bank and population data from Penn World T

So far, the results show high concentration in employment, value added a result of natural resource rents. Figure 2-3 plots predicted Gini indices a capita for various levels of resource rents to GDP shares; it shows tha relationship is maintained in most levels, and the steepest curve is th countries. However, this U-shaped relationship disappears in the hi resource rents' share in GDP (over 40%) where the concentration contin along the development path. Accordingly, the higher the resource rents' the less likely diversification could happen along the development path. Instead, concentration increases rapidly.

2.4.2 Heterogeneity across natural resources

Diversification in different sectors is likely to vary across different kinds of natural resources, since commodity prices are heterogeneous. We test the diversification affected by two groups of resources: oil and gas, and forestry.

Figure 2-3: Gini indices against GDP per capita and the share of resource rents



2.4.2.1 Oil and gas rents

Table 2-4 shows the combined results for oil and gas rents, showing an insignificant effect in employment: either ILO overall employment or UNIDO manufacturing employment. However, there is a highly significant concentration in exports (Column 4) mainly affected by oil and gas exports. There is also a significant concentration in manufacturing value added (Column 3); this concentration is found to be mostly within sectors that are highly related to oil and gas but classified individually in the UNIDO dataset[4], or sectors that produce locally consumed goods and fall within the non-tradables, as they do not show up in exports[5], which agrees with the Dutch disease model.

Table 2-5: Oil and Gas rents effects on diversification

	(1) Sectoral Employment	(2) Manufacturing Employment	(3) Manufacturing Value Added	(4) Exports
Oil & gas rents per capita	-0.003	0.001	0.002*	0.004***
	(0.002)	(0.001)	(0.001)	(0.001)
GDPpc	3754.527***	1152.295***	-466.322**	85.024
	(963.925)	(266.537)	(202.048)	(97.356)
$GDPpc^2$	1.4e+06	-1.5e+06***	9.2e+05***	-4.9e+04
	(1.8e+07)	(4.1e+05)	(3.3e+05)	(1.4e+05)
Observations	1517	1957	1869	2283
R^2	0.835	0.861	0.843	0.810

Notes: Gini index is reported. All regressions include country and year fixed effects. Oil and gas rents per capita is calculated from resource rents (World Bank) and population (PWT 8.0). Data sources: (1) Sectoral employment is from ILO, (2) and (3) manufacturing employment and value added are from UNIDO, (4) exports data is from WITS. Robust standard errors are in parentheses.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

2.4.2.2 Forestry

The effect of forest rents on diversification is different than oil and gas. As explained earlier, the sustainability and commodity prices heterogeneity might have the biggest role in this variance. Table 2-5 shows a significant positive effect of forest rents on overall sectoral employment diversification and exports (Columns 1 and 4). These results are also noted by Bhattacharyya and Collier (2014). Manufacturing employment and value added are significantly concentrated (Columns 2 and 3): this concentration

[4] Such as 9: Coke, refined petroleum products, nuclear fuels.; or 10: Chemicals and chemical products; or 12: Non-metallic mineral products; or 13: Basic Metals.

[5] Such as 1: Food and beverages; and 6: Wood products (UNIDO, 2012).

mostly falls within sectors that are highly related to forestry and agriculture but classified individually in the UNIDO dataset[6].

Table 2-6: Forest rents effects on diversification

	(1) Sectoral Employment	(2) Manufacturing Employment	(3) Manufacturing Value Added	(4) Exports
Forest Rents per capita	-6.8e+04***	8.9e+04***	5.1e+04**	-6.7e+04**
	(2.2e+04)	(2.6e+04)	(2.1e+04)	(3.0e+04)
GDPpc	-710.772	584.449***	-622.573***	922.469***
	(706.946)	(166.672)	(203.257)	(199.512)
$GDPpc^2$	6.6e+07***	-6.1e+05**	1.1e+06***	-1.5e+06***
	(1.2e+07)	(2.6e+05)	(3.3e+05)	(3.2e+05)
Instrument	*Agriculture Commodity Prices*			
Kleibergen-Paap Wald F-Stat	22.774	142.242	154.797	237.779
Stock-Yogo Critical Value	16.38/5.53	16.38/5.53	16.38/5.53	16.38/5.53
Observations	2175	2792	2716	3348
R^2	0.713	0.787	0.811	0.748

Notes: Gini index is reported. All regressions include country and year fixed effects. Forest rents per capita is calculated from resource rents (World Bank) and population (PWT 8.0). Data sources: (1) Sectoral employment is from ILO, (2) and (3) manufacturing employment and value added are from UNIDO, (4) exports data is from WITS. Robust standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

2.4.3 Heterogeneity across countries

Resource-rich countries differ in their dependence on natural resource rents, and other features are likely to influence the effect of resources, such as level of development and region. In this section, we test how this heterogeneity affects diversification.

2.4.3.1 Level of development

We start by testing the diversification across developed and developing countries. Table 2-6 combines the tested diversification in two columns for each. As shown in the table, diversification coefficients in developed countries are barely affected by resource rents. There is a slightly significant negative effect on diversification in exports and value added, but no significance in employment, either in full sample (ILO) or manufacturing

[6] Such as 1: Food and beverages; or 4: Wearing Apparel; or 5: Leather and footwear; or 6: Wood products (UNIDO, 2012).

(UNIDO). This could be explained that developed countries have a well-established manufacturing sector that would be affected in terms of exports share, but not in terms of manufacturing employment share, as the resource sector is capital intensive and would not attract employment. Meanwhile, in developing countries, resource rents have a higher significant negative effect on exports' diversification, where exports get highly concentrated. Moreover, the results show a significant negative effect on employment diversification in both sectoral and manufacturing employment. These findings show that manufactures are also exposed to being crowded out by resources, with a higher possibility in developing countries where manufacturing sectors are not highly developed, with less income and lower institutional quality than developed countries.

Table 2-7: Diversification across developed and developing countries

	(1) Sectoral Employment		(2) Manufacturing Employment		(3) Manufacturing Value Added		(4) Exports	
	developed	developing	developed	developing	developed	developing	developed	developing
Resource Rents per capita	0.001	0.003**	0.002	0.001*	0.002*	0.001	0.005***	0.002***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
GDPpc	-2.0e+03***	3.980	-5.1e+03***	526.093**	-555.099	-67.767	8669.273***	291.913**
	(666.375)	(651.843)	(1013.597)	(221.414)	(1289.122)	(228.596)	(1370.295)	(137.113)
GDPpc^2	4.6e+07***	-3.7e+06	6.5e+07***	-5.2e+05	2.6e+07*	2.7e+05	-4.3e+07**	-4.5e+05**
	(9.3e+06)	(8.5e+06)	(1.4e+07)	(3.5e+05)	(1.5e+07)	(3.7e+05)	(2.2e+07)	(2.1e+05)
Observations	997	997	1228	1859	1252	1913	1351	2665
R^2	0.695	0.863	0.865	0.787	0.773	0.781	0.774	0.688

Notes: Gini index is reported. All regressions include country and year fixed effects. Resource rent per capita is calculated from resource rents (World Bank) and population (PWT 8.0). Data sources: (1) Sectoral employment is from ILO, (2) and (3) manufacturing employment and value added are from UNIDO, (4) exports data is from WITS. Robust standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

2.4.3.2 Regions

We finally test the heterogeneity across regions, mainly by continents, in addition to the Middle East and North Africa (Mena) region. Table 2-7 shows the results in four panels. Panel A examines the effect of resource rents on ILO sectoral employment across regions, where significant diversification only happens in the Mena region, while employment in Asia, Europe and the Americas gets concentrated. However, results for manufacturing employment in Panel B are different. Manufacturing employment gets more diversified in Africa with a high significant positive effect, and more concentrated in the Americas. Asia, Mena and Europe manufacturing sectors have insignificant coefficients affected by resource rents. This might be explained by the fact that there are many resource countries located in the Mena region, and the resource effect is very high despite the small number of observations. Many of these countries have had resource rents (mainly oil and gas) for a long time before 1950, but most of them did not develop resilient manufacturing sectors, and, therefore, we can see that manufacturing employment is insignificant. We find that sectoral employment in the Mena region is diversified between government jobs, a number of services sectors and other non-tradable sectors[7]. The added value figures in Panel C are mostly matching the employment ones. Panel D shows the effect of resource rents on exports, where results indicate a high significant negative effect on export diversification. Across all regions tested, exports tend to get concentrated within the resource sector affected by resource rents, except for Asia, where exports get diversified slightly significantly.

Table 2-8: Diversification across regions

***Panel A:* Diversification across regions: ILO sectoral employment**

	(1) Asia	(2) Europe	(3) Americas	(4) Mena
Resource Rents per capita	0.029***	0.001*	0.011***	-0.008**
	(0.009)	(0.001)	(0.002)	(0.004)
GDPpc	-9.6e+03***	-1.4e+03	-3.4e+03***	4431.671
	(1716.357)	(933.953)	(1180.068)	(3672.648)
$GDPpc^2$	2.3e+08***	4.0e+07***	1.7e+08***	-1.1e+07
	(4.0e+07)	(1.2e+07)	(2.0e+07)	(2.1e+07)
Observations	469	942	619	147
R^2	0.878	0.802	0.783	0.603

Notes: Gini index is reported. All regressions include country and year fixed effects. Resource rent per capita is calculated from resource rents (World Bank) and population (PWT 8.0). All variables are divided by one billion to get shorter and easier to read results. Africa is not reported due to data limitations. Data sources: (1) Sectoral employment is from ILO. Robust standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

[7] Such as 5: Construction; or 6: Wholesale, retail trade, restaurants and hotels; or 7: Transport, storage and communication, or 8: Financing, insurance, real estate and business services, or 9: Community, social services and personal services (ILO, 2013).

***Panel B:* Diversification across regions: UNIDO manufacturing employment results**

	(1) Asia	(2) Africa	(3) Europe	(4) Americas	(5) Mena
Resource Rents per capita	-0.003	-0.062***	0.001	0.011**	0.001
	(0.008)	(0.013)	(0.001)	(0.005)	(0.001)
GDPpc	-482.336	-1.6e+04***	-5.4e+03***	1932.600	563.968**
	(1591.576)	(2781.384)	(986.506)	(1217.061)	(239.402)
GDPpc^2	5.6e+07	0.000	7.4e+07***	-1.0e+07	-6.7e+05*
	(3.8e+07)	(0.000)	(1.4e+07)	(2.0e+07)	(3.7e+05)
Observations	636	305	1185	742	387
R^2	0.757	0.921	0.863	0.916	0.721

Notes: Gini index is reported. All regressions include country and year fixed effects. Resource rent per capita is calculated from resource rents (World Bank) and population (PWT 8.0). All variables are divided by one billion to get shorter and easier to read results. Data sources: manufacturing employment and value added are from UNIDO. Robust standard errors are in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01

***Panel C*: Diversification across regions: UNIDO manufacturing value added results**

	(1) Asia	(2) Africa	(3) Europe	(4) Americas	(5) Mena
Resource Rents per capita	-0.003	-0.028***	0.001	0.011**	-0.000
	(0.007)	(0.010)	(0.002)	(0.004)	(0.001)
GDPpc	-5.1e+03***	-6.8e+03***	1000.776	3979.535*	647.138**
	(1449.360)	(1971.726)	(1355.019)	(2265.766)	(303.533)
GDPpc^2	2.1e+08***	0.000	2.7e+07	-1.5e+08***	-8.2e+05*
	(3.1e+07)	(0.000)	(1.7e+07)	(3.9e+07)	(4.9e+05)
Observations	581	385	1161	723	384
R^2	0.790	0.882	0.813	0.871	0.824

Notes: Gini index is reported. All regressions include country and year fixed effects. Resource rent per capita is calculated from resource rents (World Bank) and population (PWT 8.0). All variables are divided by one billion to get shorter and easier to read results. Data sources: manufacturing employment and value added are from UNIDO. Robust standard errors are in parentheses.* p < 0.10, ** p < 0.05, *** p < 0.01

***Panel D*: Diversification across regions: WITS exports**

	(1) Asia	(2) Africa	(3) Europe	(4) Americas	(5) Mena
Resource Rents per capita	-0.003*	0.042***	0.007***	0.010***	0.002**
	(0.002)	(0.008)	(0.002)	(0.003)	(0.001)
GDPpc	5485.706***	-3.3e+03	5238.229***	-7.7e+03***	187.529
	(689.791)	(2477.674)	(1532.717)	(1726.568)	(177.937)
GDPpc^2	-2.2e+07***	0.000	-2.2e+07	2.4e+08***	-2.2e+05
	(2.8e+06)	(0.000)	(2.3e+07)	(3.6e+07)	(2.6e+05)
Observations	803	550	1297	993	531
R^2	0.657	0.728	0.781	0.758	0.821

Notes: Gini index is reported. All regressions include country and year fixed effects. Resource rent per capita is calculated from resource rents (World Bank) and population (PWT 8.0). All variables are divided by one billion to get shorter and easier to read results. Data sources: Exports data from WITS. Robust standard errors are in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01

2.5 Conclusion

This paper examines the effect of resource rents on diversification in exports, sectoral employment, manufacturing employment and value added. The resource rents in general have a significant negative effect on diversification, and various levels of diversification occur in different economic sectors. The higher the resource rent share in a country's GDP, the less likely this country would go through the U-shaped path noted by Imbs and Wacziarg (2003). Alternatively, concentration increases rapidly through the development path.

However, there were some heterogeneous features among different country and natural resource groups. We find that there is a different effect between renewable and non-renewable natural resources on diversification. Non-renewable resources – examined by oil and gas – do not have significant effects on employment diversification, but they reduce export diversification, while renewable resources tend to increase exports' diversification and sectoral employment. We also look into different country groups: the effect of natural resources varies between developed and developing countries where manufacturing sectors are also diverse. Resource rents are likely to have higher impact on diversification within developing countries, especially in employment, where diversification gets decreased but in not affected in developed countries. However, in both country groups, resource rents reduce export diversification, indicating that manufacturing share in exports is affected in both groups, even when the manufacturing employment was not affected in the developed countries. Moreover, export diversification in all regions decreased significantly. Manufacturing diversification significantly declined in the Americas and to a lesser extent in Asia, not affected in Europe and Mena, but increased in Africa.

These results imply the presence of the Dutch disease mechanism, and are useful to policy makers in resource-rich countries who should be aware of how their labour market and exports are likely to be affected by the resource rents. Therefore, it would be very useful to test the impact of institutional quality on diversification, especially after having heterogeneous results between country groups.

Chapter 3

Diversification in Oil Countries: New Evidence on the Role of Institutional Quality

3.1 Introduction

In the first chapter of this thesis, we examined the effect of natural resource rents on diversification. We have found that along the development path, resource rents are negatively correlated with diversification, and resource countries tend to experience higher levels of concentration in exports, employment and value added. We also saw that there are heterogeneous effects of different kinds of natural resources on economic diversification. Oil and gas rents had a significant negative impact on diversification, in contrast to forestry, where the impact was significantly positive. Between different country groups, we found a significant positive impact of natural resources on diversification among developed countries, while developing countries tended to be more concentrated in exports, employment and value added. In this chapter, we extend this analysis and focus on oil and gas as the main commodity. We are mainly interested in testing the role of institutional quality on diversification when a country becomes resource abundant, driven by the heterogeneous outcomes we found between developed and developing countries in the first chapter.

The literature on the relationship between natural resources and non-resource economic activity focuses on the concept of the "Dutch Disease," which is a widely-used term in the development literature. The Economist magazine coined the term in 1977 to explain the gas boom implications on the Dutch economy. The "resource curse" was first noted by Sachs and Warner (1995, 2001), who show a significant negative relation between natural resource dependence and growth in GDP per capita. They also argue that resource abundance squeezes the manufacturing sector, as in the Dutch disease model. Other studies considered oil rents specifically: Sala-i-Martin and Subramanian (2003) find a negative relation between oil rents and economic performance. Other papers show that the impact of resource abundance is mainly driven by political factors: Tornell and Lane (1999) argue that higher than usual redistribution of natural resource endowments (voracity effect) leads to a negative impact on growth affected by the ability of powerful groups.

The related literature has three main limitations. The first is the limited number of empirical studies on economic diversification. There are a few exceptions, which include Imbs and Wacziarg (2003), Koren and Tenreyro (2007), Moore and Walkes (2010), Hausmann and Rodrik (2003), Easterly et al. (2009) and Cadot et al. (2011). However, there is a noted gap in studying the effects of natural resources on economic diversification. Secondly, most of the empirical literature on the resource curse suffers from two main identification limitations (Smith, 2015). First, a significant number of papers used resource dependency as measures of resource wealth. Lederman and Maloney (2003) point out that Sachs and Warners and other papers use resource exports' share of GDP as a measure of resource wealth, which leads to endogeneity and omitted variable problems. Lower GDP could be caused by poor growth resulting from non-resource sectors, leading to a rise in the share of resources in GDP. The second limitation is that most of these papers use cross-sectional data. Panel data studies could provide more robust results considering both time and country variations. The third limitation we find in the literature is that only a small number of papers link between institutional quality and economic diversification directly. Most of the papers study the relationship between political institutions and economic growth solely as we show below.

In this paper, we use panel data analysis to get the advantages of country and time fixed effects. However, even using this strategy is not enough, as countries could choose the quantity of oil they discover. To overcome this limitation, we only use giant oil discoveries as a source of variation. A giant oilfield discovery is deemed to contain ultimate recoverable reserves (URR) of 500 million barrels equivalent or more before exploitation[8]. We choose only oil discoveries, rather than other commodities, for a number of reasons. First, oil discoveries are widely varied in location (Wick & Bulte, 2009). Second, most recent resource discoveries have been in oil (Smith, 2015). Third, oil has been the commodity mostly associated with the resource curse in the literature.

Giant oil discoveries have three unique features (Arezki et al., 2015b). First, the relatively significant size of giant oil discoveries provides a unique source of macroeconomic news shock and is hardly predictable. Second, the production lag that exists between discovery and production (typically lasts for 4-6 years on average) makes the news shocks of discoveries a good proxy of natural resources. Third, the timing of discoveries is plausibly exogenous. We show in this paper that related macroeconomic and political features fail to predict giant oilfield discoveries.

[8] In appendix B, we show that smaller sizes of discoveries do not have any significant impacts on diversification.

This paper estimates the causal effect of giant oil discoveries as a news shock on economic diversification, and the contribution of institutional quality in this impact. Using panel analysis, we compare between countries that have discovered giant oilfields to countries that have not during the period 1962-2012. See the data section for the list of control group countries in our sample. A major concern in our design is whether oil discoveries are exogenous or not. We test if related economic and political factors could predict discoveries and we do not find any significant impacts, proving the exogeneity of giant oil discoveries.

In addition to the economic and political variables tested in this paper, one might also argue that governments or other entities could manipulate the exact timing of the announcement of a giant oil discovery. Arezki et al., (2015b) argue that this is not plausible in Mike Horn's dataset that we use in this paper, as Horn shows that these concerns about a possible manipulation have little ground. In addition, they also argue that Mike Horn's dataset is immune from such concerns, "as each discovery date included in his dataset has been independently verified and documented using multiple sources which are reported systematically for each discovery date" (p. 17). We also address the issue of the possibility that past discoveries could predict future discoveries. Arezki et al., (2015b) show that previous oil discoveries could have two opposite impacts on the possibility of current and future discoveries. First, more discoveries could increase discovery costs, reducing the likelihood of future discoveries. Second, on the other hand, previous discoveries enhance learning about the geology and therefore increase the chances of future discoveries. Accordingly, previous discoveries could have any of the noted two impacts. To control for this uncertainty and for the serial correlation that could arise between discoveries, we include the number of giant discoveries in each country from t-10 to t-1 for each discovery in year *t*, in addition to the country and year fixed effects in our empirical design. However, in case endogeneity is likely to be a concern, we run an instrumental variable estimation as a robustness check which controls for the remaining variations between countries. We find that large oil discoveries lead to export concentration after a time lag of 8-10 years after discovery.

Next, we add the institutional quality covariate to the model. This inclusion did not have a significant impact on export diversification: results are mostly unaffected. The notable difference comes in manufacturing employment, where adding the institutional quality covariate increases the concentration. In fact, we find that the institutional quality covariate has a high significant negative impact on diversification in manufacturing employment, meaning that countries with worse institutions have higher concentration in manufacturing employment after giant oil discoveries. This result runs counter to much of the literature, which argues that countries with better institutional quality receive less negative effects from natural resources, and thus are able to resist the Dutch disease. However, we find that no country is fully immune; we add in this paper that oil discoveries have a negative impact on diversification in all countries, with different impact levels on heterogeneous economic sectors as we argue in the results section.

To get into the difference between countries with higher or lower institutional quality, we follow Jones and Olken (2004) methodology in observing the Polity2 score in the year prior to the discovery year. This mechanism allows assessing the institutional quality of each government one year before discovery, to avoid any institutional changes that could occur in the same year of discovery as an endogenous effect. We find that autocratic governments are generally more negatively affected than democracies. Employment becomes more concentrated in autocracies.

This paper contributes to the literature in the following ways. First, to our knowledge, it is the first paper to test the causal impact of an exogenous measure of natural resources and institutional quality on economic diversification. Second, it is among the first papers[9] to empirically evaluate the short and long-run effects of resource discoveries on macroeconomic outcomes. Third, including the institutional quality measure in the model contributes to the literature on the correlation between institutional quality and the resource curse. Fourth, our data includes Middle Eastern countries, as Ross (2001) notes that most of the oil curse literature avoids studying the MENA countries for data limitation reasons, where the region includes a good number of main oil exporters with heterogeneous institutional quality scores.

There are five other papers which could be close to this paper by using the same source of variation: Lei and Michaels (2014), Arezki et al., (2015 a-b), Smith (2015), and Cotet and Tsui (2013). There are three main differences between our paper and these papers. First, our paper is the first to test the impact of giant oil discoveries on economic diversification, while Lei and Michaels (2014), Cotet and Tsui (2013) and Arezki et al., (2015a) study the discoveries' impact on conflict, and Arezki et al., (2015b) study the impact on macroeconomic outcomes, and Smith (2015) studies the impact on GDP growth. Second, our paper follows both Lei and Michaels (2014) and Arezki et al., (2015b) in using all giant oil discoveries a country experiences, whereas Smith (2015) uses only the first discovery that makes a country resource-rich. Third, we add a covariate of institutional quality in the model following Mehlum et al. (2006), whereas the previous papers do not.

The rest of this paper proceeds as follows: the following section views a theoretical introduction to the resource curse, Dutch disease and the role of institutional quality.

[9] Lei and Michaels (2014), Arezki et al. (2015b), Smith (2015)

Section 3 views related papers on oil discoveries and the impact of institutional quality on the resource curse. Section 4 provides a brief background of the oil industry. Section 5 describes our data. Section 6 outlines our empirical strategy. Section 7 presents the main results and discussions. Section 8 concludes.

3.2 Theoretical Introduction

Many papers in the resource curse literature argue that the experiences of resource rich countries have been heterogeneous. Some countries used their resource revenues to improve the local economy, while others ended up with worse situations[10]. In this section, we illustrate the model suggested by Van der Ploeg (2011) to describe the impact of a resource windfall on an open economy. The theory suggests that Dutch disease occurs when the extra wealth coming from natural resource sales leads to real exchange rate appreciation and contraction of the non-resource tradable sector (Corden & Neary, 1982).

The model depends on a two-sector economy with a resource windfall, abstracting from capital accumulation, international investment and financial assets. There are two kinds of goods: tradable (T) and non-tradable (N). The equilibrium in the tradable sector happens when exports of resources equals net imports of tradable goods: $H_tQE=Ct-H_tF(L_t)$ where H_t is productivity in the tradable sector, Q is the natural resources international price, E is the volume of exports of natural resources, C_t is the consumption of tradable goods, L_t is the employment share in the tradable sector, making $H_tF(L_t)$ the output of the tradable sector. Non-tradable goods market equilibrium requires $Cn=H_nG(L_n)$, where C_n denotes consumption of non-tradable

[10] This section heavily depends on Van der Ploeg (2011) and Mehlum et al. (2006).

goods, H_n productivity in the non-tradable sector, L_n employment in the non-tradable sector and $H_nG(L_n)$ output of the non-tradable sector. Labour market equilibrium requires $L_t+L_n=1$ conditioning labour mobility between the tradable and non-tradable sectors, where total labour supply is normalised to 1. Households maximise utility $U(C_n, C_t)$ subject to the budget constraint $PC_n+C_t=Y$, where P is the relative price of non-tradable goods in terms of tradable goods, and Y is the national income $Y \equiv PH_n G(L_n)+H_t F(L_t)+H_t QE$. Optimality requires $U_n/U_t=P$. With CES utility, we have $C_n=Y/(1+P^{\varepsilon-1})P,$ where ε is the elasticity of substitution between tradable and non-tradable goods. The equilibrium condition in the market for non-tradable goods is,

$$H_nG(L_n)=Cn= Y/(1+P^{\varepsilon-1})=[PH_N G(L_N)+H_T F(L_T)+H_T QE\ Y](P+P^{\varepsilon}),$$

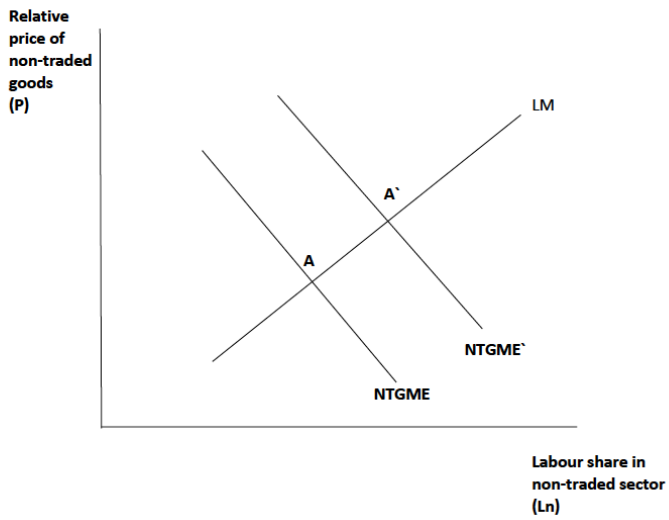
That yields $P^{\varepsilon}=H[F((1-LN))+QE]/G(LN),$ where $H \equiv H_T/H_N$ is the productivity of the tradable and resource sectors relative to that of the non-tradable sector. This equation is illustrated in Figure 3-1 where NTGME (non-tradable goods market equilibrium) shows the combination between real exchange rate (P) and the share of labour in the non-tradable sector L_n (x-axis). The NTGME slopes downwards, showing that a higher P is associated with relatively lower demand for non-tradable goods and thus lower employment in the non-tradable sector. Labour mobility between the tradable and non-tradable sectors requires equal pay, so the value of the marginal product of labour is the same between the sectors. The LM (labour market) curve slopes upward, showing that a higher relative price of non-tradable goods (higher P) increases the marginal product of employment in the non-tradable sector, so employment in the tradable sector must decline in order to push up the marginal product of labour in the tradable sector.

We now consider a resource windfall. Higher natural resource revenue QE boosts national income and demand, shifting the NTGME upwards, while LM is unaffected.

The equilibrium shifts from A to A`. Two spans of consequences are considered: short run consequences and long run consequences. Consequences in the short run are:

1. Higher resource revenues push for higher relative price of non-tradable goods, and thus an appreciation of the real exchange rate, and for a decline in the tradable sector and expansion of the non-tradable sector.
2. Labour shifts from the exposed to the sheltered sectors (non-tradable). This boosts consumption and output of the non-tradable goods.
3. Higher resource revenues could also possibly increase imports, which adds to the rise in consumption of tradable goods.
4. National income rises by more than the natural resource revenues, affected by the increase in consumption, and thus, welfare rises boosted by resource revenues.
5. Consequently, the labour market will have higher concentration in the non-tradable sector, and a higher concentration in resource exports considering the production gap.

Figure 3-1: Natural resource dependence and labour movements



Notes: a resource boom shifts A to A`, so is a shift from the tradable to non-tradable sector and real exchange appreciation.

In the long run, we must allow capital and labour to be mobile across sectors, we assume the economy to be an open economy with Heckscher-Ohlin framework which should have competitive labour, capital and product markets, and production does not use any resources, and there are constant returns to scale in the production of tradable and non-tradable goods. A rise in resource windfall increases wage-rental ratio if the non-tradable sector is more labour-intensive than the tradable sector. There is a rise in the relative price of non-tradable goods leading to an expansion of the non-tradable sector and a contraction of the tradable sector. Labour and capital shift from the tradable to non-tradable sectors, leading to higher concentration in the non-tradable sector.

We now consider the case when the resource sector uses labour and capital as factor inputs. The short-term consequences as per the Dutch disease model would be as described *spending effects* of a resource boom, where the direct impact would be an appreciation of the real exchange rate as defined earlier. Another outcome is the *resource movement effects,* which occur as a result of the spending effect and also of labour movement from tradable and non-tradable sectors into the resource sector. In the long run, we assume both labour and capital are mobile between the tradable and non-tradable sectors, and the resource sector only uses labour.

Related to the resource movement effect, the Rybczinski theorem states that the movement of labour out of the non-resource towards the resource sectors causes output of the capital-intensive non-resource sector to expand. This could lead to two different scenarios:

1. Pro-industrialisation: if the non-resource sector was mainly tradable and capital-intensive manufacturing, when labour moved out to the resource sector, the capital-intensive output increases.

2. De-industrialisation: if the non-resource sector was mainly non-tradable and capital-intensive, when labour moved from the tradable to the resource sectors and output declines, the real exchange rate depreciates. The non-tradable sector will expand (as per Rybczinski's theorem), which also pushes real exchange rates to depreciate. Expansion of the non-tradable sector increases its output, which also fuels the depreciation of the real exchange rate. And finally, real exchange rate depreciation may also result from a boost to natural resource exports if the tradable sector is relatively capital intensive and capital is needed for the exploitation of natural resources. Since less capital is available for the tradable sector, less labour is needed and more labour will be available for the non-tradable sector (more output), which also leads to a depreciation of the real exchange rate. A final channel that could lead to real exchange rate depreciation is through income distribution, with a shift towards consumers with a low propensity to consume non-tradable goods.

The final impact would be the shift from A to A`, where higher natural resource exports lead to real exchange rate appreciation and expansion of the non-tradable sector. All of this leads to higher export concentration in the resource sector, and a higher employment concentration in the non-tradable sectors. If the country did not have any significant resource booms earlier, we assume that the labour is diversified between a number of tradable and non-tradable sectors. Preceding a resource boom, labour and trade in the long run move towards certain sectors: resource sector in exports, and non-tradable sectors in the labour market. We now consider the role of institutional quality in dealing with these movements, using a model by Mehlum et al. (2006).

The resource curse and the institutional quality

We follow the model illustrated by Mehlum et al. (2006) to describe the role of institutional quality in influencing the resource curse. The model differentiates between two types of institutions in resource-rich countries: grabber friendly and producer friendly. Grabber-friendly institutions are where rent seeking and production are competing activities, and producer-friendly institutions are where rent seeking and production are complementary activities. Grabber-friendly institutions have gains from specialising in unproductive influence activities, for instance due to a weak rule of law, malfunctioning bureaucracy, and corruption. Grabber-friendly institutions can be particularly bad for growth when resource abundance attracts scarce entrepreneurial resources out of production and into unproductive activities. With producer-friendly institutions, rich resources attract entrepreneurs into production, implying higher growth. Mehlum et al. (2006) are in contrast to the rent-seeking story by Sachs and Warner (1995) where resource abundance leads to a deterioration of institutional quality in turn lowering economic growth. Mehlum et al. (2006) argue that institutions may be decisive around how natural resources affect economic growth even if resource abundance has no effect on institutions, and that natural resources put institutions to the test, so that the resource curse only appears in countries with inferior institutions.

The analysis of Mehlum et al. (2006) argues that the differences in growth between resource-rich countries with good institutions and the ones with bad institutions are primarily due to how resource rents are distributed via the institutional arrangement. This is also what Acemoglu and Robinson (2001) argues in assessing the decisive role of institutions for economic development. Using this analysis, we argue that resource-rich countries with good institutions are more able to allocate rents into productive entrepreneurs in a producer friendly institutional setting.

The parameter λ in the model denotes the institutional quality, which reflects the degree to which the institutions favour grabbers versus producers. Formally, λ measures the resource rents accruing to each producer relative to that accruing to each grabber; $\lambda = P/G$ where P is the rent allocated to producers, and G is the rent allocated to grabbers. N is the total number of entrepreneurs: $N = n_P + n_G$.

When $\lambda=0$, that means the system is completely grabber friendly (P=0), such that grabbers extract the entire rent, each of them obtaining R/n_G. A higher λ implies a more producer friendly institutional arrangement (higher P).

When $\lambda=1$, there are no gains from specialising in grabbing as both grabbers and producers each obtain the share R/N of resources (as P=G).

Accordingly, $1/\lambda$ indicates the relative resource gain from specialising in grabbing activities. When λ is low in some countries, the relative gain from specialising in resource grabbing ($1/\lambda$) is large. In countries where λ is higher, the resource gain from specialising in grabbing becomes lower, and the entrepreneurs are less willing to give up the profit from production to become grabbers.

The payoff to each grabber is: $\pi_G = sR/N$, where s is a factor decreasing in λ since each grabber gets less the more producer friendly the institutions are, as each producer's share of the resource rent is $\lambda sR/N$. There is also a positive effect on s from less competition between grabbers.

The producers' profits π_P are the sum of profits from production π and the share of the resource rents $\lambda sR/N$. Hence,

$\pi_P = \pi + \lambda s(\alpha, \lambda)R/N.$

We now turn to the productive side of the economy, since we are interested to know how natural resources affect incentives to industrialise. There are L workers and M different goods; each one can be produced in a modern firm or a competitive fringe.

There will be an institutional quality threshold λ = λ* that determines in which equilibrium an economy ends up:

$$\lambda * \equiv \frac{R}{R + N\pi(N)}$$

and we have the following propositions:

1. When institutional quality is high, $\lambda \geq \lambda^*$, the equilibrium is production friendly. And when institutional quality is low, $\lambda < \lambda^*$, the equilibrium is grabber friendly.

This proposition shows how natural resources put the institutional arrangement to a test. The higher the resource rents *R* relative to the potential production profits $N\pi(N)$, the higher the institutional quality threshold λ^*. Accordingly, more resources require better institutions to avoid the grabber equilibrium.

2. More natural resources is a pure blessing in a production equilibrium – a higher *R* raises national income. More natural resources is a curse in a grabber equilibrium – a higher *R* lowers national income.

3. In the grabber equilibrium ($\lambda < \lambda^*$*), more producer-friendly institutions (higher values of* λ*) increase profits both in grabbing and production, and thus lead to higher total income. In the production equilibrium (*$\lambda \geq \lambda^*$*), a further increase in* λ *has no implications for total income.*

4. In the grabber equilibrium, a higher number of entrepreneurs N raises the number of producers n_p, lowers the number of rent-seekers n_G, and leads to higher profits in both activities.

This proposition states that a higher number of entrepreneurs is a double blessing. New entrepreneurs get into production, and they also squeeze the grabbers' share to shift over to production. The reason is the positive externality in modern production.

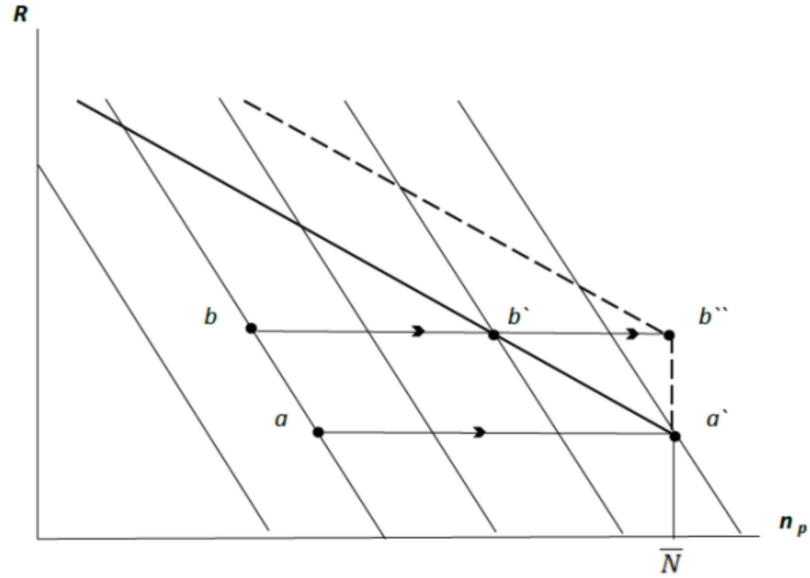
To see how the dynamics work, consider Figure 3-2, where it measures the number of productive entrepreneurs n_p on the horizontal axis and the value of resources R on the vertical axis. The long-run relationship between R and n_p is:

$$R = \frac{\overline{N}}{1-\lambda}\pi(n_p) - n_p\pi(n_p)$$

In the producer equilibrium, n_p is by definition equal to $\overline{N}$. Thus, the long-run relationship in Figure 3-2 has a kink for $n_p = \overline{N}$. The kink defines the separation between the grabber and the producer equilibrium and is thus given by R^*. The long-run relationship between R and n_p is given by the bold curve in the figure.

The figure also has iso-income curves. Each curve is downward sloping, as more natural resources are needed to keep the total income constant when the number of producers declines.

Figure 3-2: Resources and rent seeking



The model assumes that we have two countries, A and B, where they have the same quality of institutions (the same λ), and the same initial income level. Country A has few resources, but a high number of producers, while country B has more resources and fewer producers. Country A, which starts out at point a, ends up in point a`. While country B, which starts at point b, ends up in point b`. The figure shows that the resource-rich country B ends up at a lower income level than the resource poor country A. The reason is that country A, because of its lack of resources, ends up in the production equilibrium, while country B, because of its resource abundance, ends up in the grabber equilibrium. Accordingly, over the transition period, growth is lowest in the resource rich country. This is a specific example of a more general result. As provided in proposition 2, country B would increase its growth potential if it had fewer resources.

Next, we assume that country B instead had more producer-friendly institutions and thus a higher λ than country A. As country B now is more immune to grabbing, it can tolerate its resource abundance and still end up in the production equilibrium. As a result, the long-run curve for country B shifts up, as illustrated by the dotted curve in the figure. With grabber-friendly institutions (low λ), country B converges to point b`, while with producer-friendly institutions (high λ), country B converges to b``. Income is higher in b`` than in b`. Over the transition period, growth is therefore highest with producer-friendly institutions. Moreover, with more producer-friendly institutions, the resource-rich country B outperforms the resource-poor country A, eliminating the resource curse. If country B was successful in being immune to grabbing, it would allocate more resources towards producer-friendly institutions, and therefore having less concentration in the non-tradable sector. As described earlier, producer-friendly institutions encourage growth in the productive tradable sector and therefore lead to less concentration in the non-tradable sector affected by the resource movement effect.

To explain these diverging experiences in the long run, Figure 3-3 plots the relative employment share in non-tradable to tradable sectors versus resource abundance in our dataset using the ILO sectoral data. We try to illustrate labour movements between tradable and non-tradable sectors[11]. Panel (a) shows that the more the country is dependent on oil, the higher the share of labour is in the non-tradable sector. Panel (b) shows that oil countries with better institutions do not experience a big shift between tradable and non-tradable sectors, as the slope remains almost flat. Panel (c) shows that oil countries with bad institutions experience the resource movement effect in the long run, as labour moves from tradable to non-tradable sectors, shown by the higher relative employment share of non-tradable to tradable sectors.

[11] From the ILO dataset (ISIC-revision 3), we identify five sectors to be tradable sectors: (1) Agriculture, hunting, forestry and fishing; (2) Mining and quarrying; (3) Manufacturing; (4) Electricity, gas and water supply; and (6) Wholesale and retail trade, restaurants and hotels, repair of motor vehicles. The remaining four sectors are non-tradable: (5) Construction; (7) Transport, storage and communication; (8) Financing, insurance real estate and business services; (9) Community, social and personal services. This classification between tradable and non-tradable sectors is based on the European Commission Annual Macro-Economic Database (AMECO). The full regression results are shown in the results section.

Figure 3-4 plots the relative concentration in resource to non-resource exports[12]. We can see from the three panels that there are no major differences between countries with bad institutions or countries with better ones. The figures indicate that all resource-rich countries experience a shift towards a higher share of resource exports compared to other types of exports, while the experience varies in terms of employment and structural change.

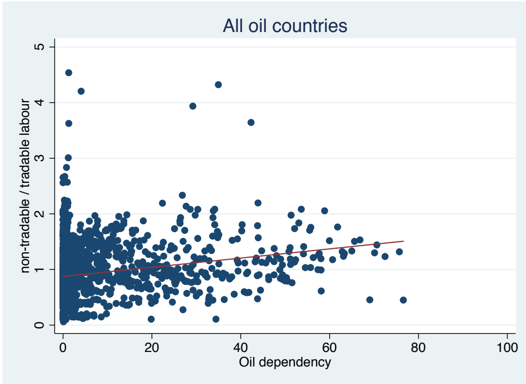
On this basis, we emphasise that the variance of structural change performance among resource-rich countries is mainly due to how resource rents are distributed via the institutional arrangement. This variance leads to different concentration outcomes in tradable and non-tradable sectors, affecting growth in the long term.

The hypothesis of the role of institutional quality on growth is consistent from observations of several countries. Many papers in the literature take the example of Norway and Botswana as two resource-rich countries that have been successfully growing and reversing the resource curse theory. Norway has turned from the poorest in Europe in the beginning of the 20th century to one of the richest around the world lately. Botswana has one of the highest growth rates since 1965 (Acemoglu & Robinson, 2001). The literature relates this extraordinary performance to the high level of institutional quality. In the data section, we show the impact of resource abundance (oil discovery in this paper) on export and employment diversification.

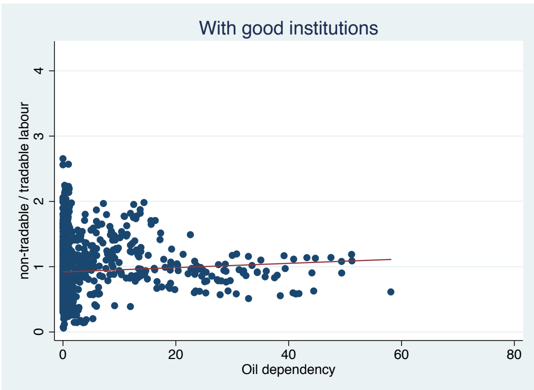
[12] From WITS dataset (SITC 1-digit), we identify two sectors to be resource sectors: sector 3. Mineral fuels, lubricants and related materials; and sector 9. Commodities and transactions not classified elsewhere in the SITC.

Figure 3-3: Oil, the Dutch disease and institutions–(a) all oil countries, (b) with good institutions (c) with bad institutions

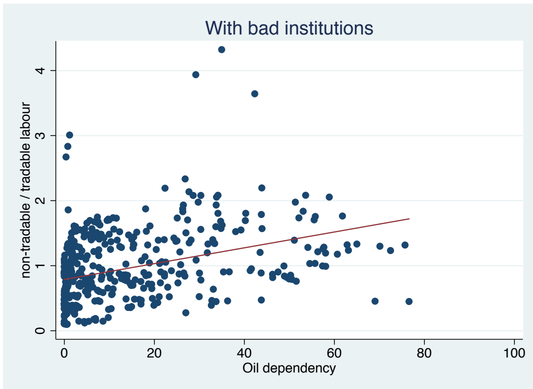
(a)



(b)



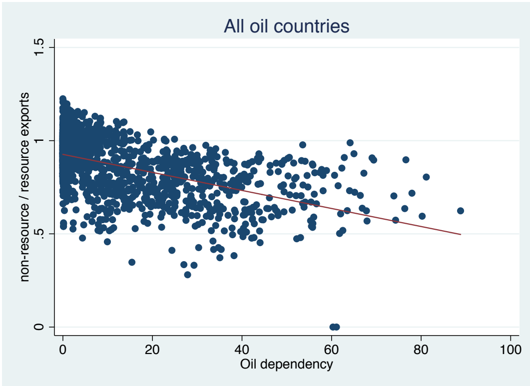
(c)



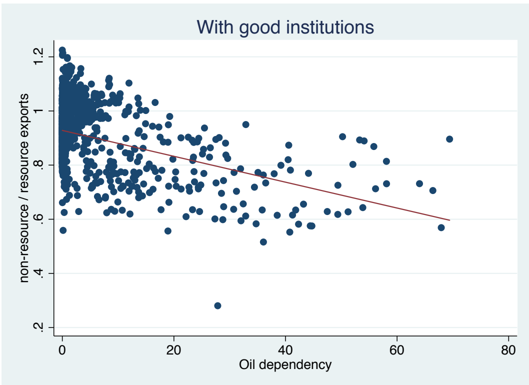
Notes: Resource movement effect is experienced as labour moves from tradable to non-tradable sectors with higher oil abundance. X-axis is oil dependency measured by oil rent share in GDP, data from the World Bank. Y-axis is the relative employment share in non-tradable to tradable sectors within the ILO data. Panel (a) includes all countries in our dataset. Countries in panel (b) are: Australia, Austria, Canada, Colombia, Czech Republic, Denmark, France, Georgia, Germany, Greece, Israel, Italy, Japan, Lithuania, Malaysia, Netherlands, Norway, Serbia, Slovak Republic, Slovenia, Trinidad and Tobago, Turkey, Ukraine, United Kingdom, United States of America, Venezuela. Countries in panel (c) are: Algeria, Angola, Azerbaijan, Bahrain, Belarus, Cameroon, China, Cuba, Egypt, Gabon, Iran, Kazakhstan, Kuwait, Morocco, Oman, Poland, Qatar, Saudi Arabia, Syria, Tunisia, United Arab Emirates, Uzbekistan, Vietnam.

Figure 3-4: Export concentration between resource and non-resource sectors with increasing oil dependency

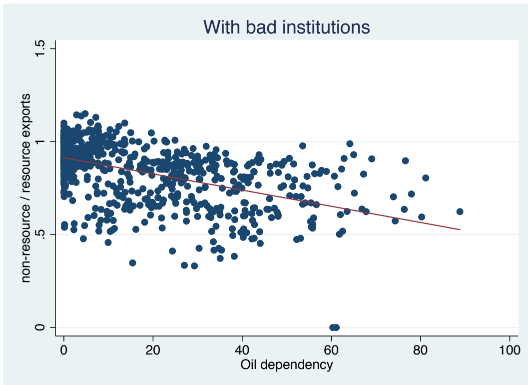
(a)



(b)



(c)



Notes: concentration in resource exports, in all regime types. X-axis is oil dependency measures by oil rent share in GDP, data from the World Bank. Y-axis is the relative non-resource to resource exports from the WITS dataset. Panel (a) includes all countries in our dataset. Countries in panel (b) are: Australia, Austria, Canada, Colombia, Czech Republic, Denmark, France, Georgia, Germany, Greece, India, Israel, Italy, Japan, Lithuania, Malaysia, Netherlands, Norway, Russian Federation, Slovak Republic, Slovenia, South Africa, Sweden, Trinidad and Tobago, Turkey, Ukraine, United Kingdom, United States of America, Venezuela. Countries in panel (c) are: Algeria, Angola, Azerbaijan, Bahrain, Belarus, Cameroon, China, Congo Rep., Cote d'Ivoire, Cuba, Egypt, Gabon, Iran, Iraq, Jordan, Kazakhstan, Kuwait, Libya, Morocco, Oman, Qatar, Saudi Arabia, Syria, Tunisia, Turkmenistan, United Arab Emirates, Uzbekistan, Vietnam.

3.3 Related literature

A few recent papers have included oil discoveries into their specifications aiming to study the resource curse. Lei and Michaels (2014) find that giant oilfield discoveries lead to armed conflict. They use giant oil discoveries as a measure for natural resources, as they argue it is exogenous and could give more reliable results. A related paper with a different outcome is Cotet and Tsui (2013), where they use discoveries at all sizes and find no relationship between oil wealth and civil war. They agree with Lei and Michaels (2014) by arguing that the fixed effects model does not estimate the causal effect of oil on civil war, because oil exploration might be endogenous in that case. To handle this problem, they extend the analysis to instrument oil wealth by natural disasters. Arezki et al., (2015b) follow Lei and Michaels (2014) by restricting the oilfield discoveries to the giant ones. They claim that giant oil discoveries provide "a unique source of macro-relevant news shocks," as they test the impact of oil discoveries on a number of macroeconomic outcomes using the ARDL model.

Several recent papers in the resource curse literature have challenged the idea that resources harm development (Brunnschweiler & Bulte, 2009); (Smith, 2015). One concern in recent literature is that using resource share of GDP or exports as measures for resource dependency creates an endogeneity problem. Alternatively, Smith (2015) uses oil discoveries as an indicator of oil wealth, and restricts the sample to cover only the first discovery that raises the country's revenues significantly. The paper uses a difference-in-difference analysis to find that following an oil discovery, there is a positive effect on GDP per capita in the long term. Michaels (2011) investigates the impact of resource abundance on growth in the U.S. southern counties over the long term. He finds that oil wealth caused the U.S. south to catch up with the north's development. He uses large oil discoveries as a measure of oil abundance, aiming to get an exogenous source of variation. Further results show that oil abundance in these counties increased the employment share of mining, shifting employment from agriculture to manufacturing – which includes mining jobs – especially after the year 1940. Moreover, the paper gives some explanation to that rise by showing an increase in population density in oil counties, caused by migration from other counties. An argument that could be raised in these papers is whether these discoveries were proven resources or only estimates. This depends on how thoroughly a given country has been prospected, and this could also be affected by the country's wealth and institutions. This concern could also arise in this paper, and we argue that our empirical design controls for time-invariant factors present before and after discovery. We also control for previous discoveries in the last ten years to emphasise the country's position in terms of oil wealth and institutions prior to large oil discoveries.

A number of papers have studied the correlation between natural resources and political outcomes. Mehlum et al. (2006) use an institutional quality index to assess the impact of natural resources on growth, relying on the quality of institutions in a cross-country setting. Empirically, the paper shows that natural resources reduce income in countries with lower institutional quality, while income rises in resource countries with better institutions, such as in Norway, Canada and Australia. The institutional quality index they used is an average of five indices: rule of law index, a bureaucratic quality index, a corruption in government index, a risk of expropriation index and a government repudiation of contracts index. We show below that we use "Polity 2" from the "Polity IV" dataset to measure institutional quality instead of the weighted index proposed by Mehlum et al. (2006). Polity 2 gives a score from -10 to 10 to measure democracy in countries up to 2012. Jones and Olken (2004) test if development is affected by individual leaders, through using the leader's death as an exogenous variation. They find that leaders have a significant impact on growth in autocratic governments but not in democratic ones. We follow this paper in classifying governments and by using Polity data as a measure for institutional quality. Apergis and Payne (2014) focus on the MENA region to study the correlation between growth in oil-abundant countries and institutional quality. By using time-series analysis, they find that growth is more negatively affected in labour-importing countries than labour-abundant countries within the region. The paper emphasises the role of transparency and labour market liberalisation in enhancing the overall economic welfare. Williams (2011) tests if growth is affected by transparency, as a measure for institutional quality. He argues that lack of transparency can harm growth through less foreign direct investments and more corruption.

Other recent papers study the political resource curse through tracking inflows and outflows in regional budgets. Caselli and Michaels (2013) track oil revenues in Brazilian municipalities to see how they would affect living standards and public goods such as education, housing and infrastructure. By using cross-region analysis, they find that a fraction of the oil revenue disappears before reaching public goods and services, as inflows and outflows do not match in municipalities' budgets. The paper provides a full analysis of oil windfalls and uses multiple specifications, but its main limitation is the use of cross-region analysis instead of a panel, which could provide more robust results in terms of variation and exogeneity. Contrary to these findings, Cavalcanti et al. (2014) provide evidence of an increase in GDP per capita in Brazilian municipalities that produce oil. They follow Caselli and Michaels (2013) in studying the impact of oil production and discovery on public goods and services. The paper finds no evidence for a Dutch disease style crowding out of the manufacturing sector. Their results indicate an increase in average wages and worker density, and in local services. They also argue that the impact of oil wealth depends strongly on the institutional setting.

The nature of incumbents also matter in influencing the relationship between resources and economic outcomes. Economic analyses of government are divided into two groups (Besley, 2007). One emphasises government in the public interest. It focuses on what governments can do to improve the living standards of their citizens. Government supports the market system by establishing the basic judicial regulations and property rights. Government can support the private sector through regulating interests out of the private sector's scope. Government can offer public goods that cannot be fully provided by the local market. In the second group, government is taken as private interest and a rent seeking target. Government might fail to keep the officials away from corruption, which leads to consequences against the citizens' interests. Good government is partly initiated by good institutions, but it is highly affected by good leaders. To proceed with these questions, the main requisite is to study a model of how government allocates resources. A major difference between democracies and autocracies lies in the way the information is collected. For any kind of government, powerful, organised groups seem to be a big source of influence on government decisions. In addition, size of government is not hugely different between democracies and autocracies. Besley (2007) also concludes that democracy comes in many forms, and looking for an effect of democracy is probably misguided. He emphasises the concept of government failure, which "refers to problems that arise when one actor in the economy (the state) monopolizes the legitimate use of force" (p. 46). In addition, he stresses that while markets have their limits in allocating resources, so do governments. Acemoglu et al. (2003) address these issues and study macroeconomic performance in different governments. They show that countries with bad institutional quality "state failure" go through more volatile business cycles. They also highlight the importance of other factors listed in the literature, such as technology, in curbing volatility but still stress on the institutional quality as the main factor.

Ross (2012) shows that it is true that institutional quality in oil countries is lower, but it is not because of oil revenues per se. Ross (2012) argues that oil countries not only need better institutions to manage oil revenues, they need exceptionally strong ones that should be developed in a short time. There are also several papers that discuss political elite behaviour to explain political outcomes. Acemoglu et al. (2003) and Acemoglu and Robinson (2001) show that higher resource rents lead to higher political stakes, making the political elite unwilling to improve current political and economic policies. The elite do that in order to sustain their shares in rent seeking in the future.

A number of other papers emphasise the role of institutional features in economic growth. Knack and Keefer (1995) show that property rights have a big impact on investment and growth. Bhattacharyya and Hodler (2014) find that resource rents are negatively correlated with financial development in countries with lower scores of Polity2, showing that resource-rich countries could be financially underdeveloped. Mauro (1995) finds a negative relationship between corruption and growth through cross-country data. Hall and Jones (1999) find a close relationship between output per worker and government policies. Klomp and de Haan (2009) find a negative relationship between democracy and economic volatility.

Although recent papers on natural resources have provided more convincing empirical designs and models, the issue of endogeneity is still very plausible. We argue that the approach we follow in this paper is most likely to be exogenous for several reasons. First, the fixed effects model controls for any differences in the main characteristics before and after the giant oil discoveries. Second, as we show in the next section, none of the main country characteristics could predict giant oil discoveries. Third, we did not find any significant differences between treatment and control groups before and after giant oil discoveries, and the empirical design controls for time-invariant factors present before and after discovery.

3.4 A brief on oil discoveries

In this section, we go through the background of the oil industry, and how explorations expanded geographically. We argue that the new giant oil discoveries are exogenous: not driven by a single country and mainly caused by global factors[13].

In 1859, Edwin Drake found oil in the first drilling attempt to solely look for oil in Pennsylvania. Before that, oil was usually collected from water surfaces and used mainly for medicine. The main origins of oil go back to 3000 B.C. in various parts of the Middle East, precisely in Babylon, and the site of modern Baghdad. Following Edwin Drake's historical oil discovery in 1859, the oil industry was mainly developed within the United States, and later in Russia and some parts of East Asia. With the rise of World War 1, the demand for oil increased and thus the exploration attempts, which led to new discoveries all over the world. The higher demand helped improve new technologies facilitating the expansion of new discoveries. By the 1920s, the sub-surface structure became easier as the seismograph was invented. The number of oil discoveries in the United States surged due to this invention and other technologies such as aerial surface plotting and micropaleontology. However, these technologies were not used to good effect in other locations as they did in the United States at that time, as Saudi Arabia was reported in 1926 to be "devoid of all prospects for oil" by a British geological survey. Despite the expansion of oil discoveries around the world, only eight countries accounted for 94 percent of world oil production by 1938, with the United States dominating two thirds of this share.

Following World War 2, discoveries expanded for a number of reasons. First, it has been argued that the access to oil was the main driver for the allied victory, as governments needed oil for their armies more than for commercial purposes. This led

[13] This section borrows heavily from the book *The Prize* by Daniel Yergin, and the book *The Oil Curse* by Michael Ross, and Smith (2015).

countries to expand into Africa during the 1950s; for example, France began to expand the oil industry within its African colonies. Despite the perception that Africa would not be a sufficient provider of oil, discoveries began to strike in the 1950s. France discovered oil in its colonies Gabon and Algeria, followed by Nigeria in 1956. These findings changed Africa's status, to be seen as the "new frontier" of oil, leading to more major discoveries in Libya and the Republic of Congo, and more in other areas.

Second, after the World War 2, countries focused on rebuilding their economies, increasing the demand for oil. Main drivers were the rising income and the expanded use of automobiles and other industries. Demand for oil increased by more than 550 percent between 1949 and 1972. By 1970, the oil industry was more distributed, driven by the order of the "seven sisters," the seven giant companies that controlled nearly the entire oil industry[14], but at least that increased the competition around the world. Moreover, barriers to entry and risk declined, affected by advancements in technology. Some of these developments during the twentieth century were geochemistry, sedimentology, satellite imaging, and computing. Another major development that happened in the 1960s and 1970s is the creation of a coalition by the developing oil producing countries in the form of the Organisation of Petroleum Exporting Countries (OPEC). Moreover, most of the oil-exporting countries in the developing world nationalised their oil industries, and established state-owned companies to run them. These developments transformed the oil industry and the status of oil producing countries, introducing more power within oil producers around the world. Ross (2012) notes that historically, high-income countries have been about 70 percent more likely to produce oil than low-income countries. Nationalisation drove international oil companies to look for new discoveries in low-income countries to be able to meet the

[14] The seven companies were Standard Oil of New Jersey (later Exxon), Standard Oil of California (later Chevron), Anglo-Iranian Oil Company (later BP), Mobil, Texaco, Gulf, and Royal Dutch Shell. These companies merged later into a smaller number of companies.

rising global demand. That has shifted the oil distribution in the recent decades towards countries with lower income. Ross (2012) also notes that the number of oil producing countries has been steady during the period between 1976 to 1998, ranging between 37 and 44 countries. That number jumped from 38 in 1998 to a record of 57 in 2006. Most new producers were low- and middle-income countries. The entrance of more poor countries had shifted the average of income in all oil producing countries from $5200 per capita in 1998 to $3000 in 2004, Ross (2012) concludes.

Another major step in the oil industry was the deep-water drilling that developed after the war. Offshore drilling attempts started by trying to find wells in shallow water near the coast during the second half of the 19th century. Major attempts occurred in 1947 off the coast of Louisiana. Giant gas fields discovered onshore in the Netherlands led to offshore discoveries in the North Sea, of which the first discovery was in 1970. The North Sea discoveries were supported when geologists realised that the North Sea floor had similar geology to the land. By that time, offshore drilling technologies improved notably and the major discoveries were made around the world, even in countries that did not have oil before such as Malaysia, the United Kingdom, Equatorial Guinea, Denmark and Norway.

In brief, we argue that giant oil discoveries are exogenous to a single country and driven by global factors, such as advancement in technology and increased demand. Moreover, Smith (2015) finds that oil prices have no impact on major discoveries, as most of the discoveries occurred before the price hike in the 1970s; before that time, oil prices were fairly low.

However, we agree with Smith (2015) that the distribution of discoveries can be predicted on some occasions. Some African countries suffered from shortage in infrastructure after the war era, making it difficult for any attempt at exploration. But that depended on whether the country was a French or British colony or not. As discussed earlier, colonies had discoveries back in the 1950s, earlier than the remaining African countries, due to the availability of required infrastructure. To address this issue, we use country fixed effects to control for the country-wide differences, and time fixed effects to control for the timing of some discoveries.

3.5 Data

We use a dataset on oil discovery from Lei and Michaels (2014), which is based on a dataset by Horn (2003, 2004). Horn reports the date of discovery, the name of the discovering country, and a number of other variables, for 910 giant oilfields discovered both onshore and offshore from 1868 to 2003. To qualify as a giant, an oilfield must have contained ultimate recoverable reserves of equivalent to at least 500 million barrels of oil. To avoid measurement error, Lei and Michaels (2014) constructed an indicator for whether a country is mentioned in the dataset as having discovered at least one giant oilfield in each given year.

Table 3-1 and Figure 3-5 show that discoveries peaked in the 1960s and 1970s, and a double-digit number of oilfield discoveries boomed in the late 1990s. Of the 910 giant oilfields covered in Horn (2004), and 782 covered in Lei and Michaels (2014), 364 are used in this paper to cover the period 1962-2003. This limitation is due to the data availability offered by UNIDO, ILO and WITS, where the earliest data available is 1962. However, our data on diversification continues up to 2012, to assess the impacts of discoveries that occurred during the 2000s in the long run, which is 8 to 10 years after discovery, as we show in the results.

Table 3-1: Number of one or more giant oilfield discoveries (from 1962 to 2003), by year

Year	Number of giant oilfield discoveries	Year	Number of giant oilfield discoveries	Year	Number of giant oilfield discoveries	Year	Number of giant oilfield discoveries	Year	Number of giant oilfield discoveries
1962	9	1971	14	1980	14	1989	7	1998	11
1963	11	1972	9	1981	6	1990	9	1999	15
1964	13	1973	11	1982	7	1991	6	2000	12
1965	16	1974	9	1983	5	1992	8	2001	8
1966	9	1975	12	1984	6	1993	4	2002	7
1967	9	1976	10	1985	7	1994	4	2003	6
1968	9	1977	11	1986	3	1995	9		
1969	12	1978	7	1987	4	1996	7		
1970	11	1979	9	1988	4	1997	4		

The data contains 364 country-year observations, with giant discoveries accounting for 5.2% of total observations. Table 3-2 shows that giant oilfield discoveries are rare events in most countries, and country-year pairs with discoveries were most common in Asia (40%), followed by Africa (17%), Europe (19%), South America (10%), North America (9%) and Oceania (5%). The treatment group is countries that have had at least one giant oil discovery during the study, which consists of 64 countries, whereas the control group is the countries that have never had any giant oil discoveries during that time which consists of 72 countries, providing a balanced comparison.

Figure 3-5: Number of one or more giant oilfield discoveries (from 1962 to 2003), by year

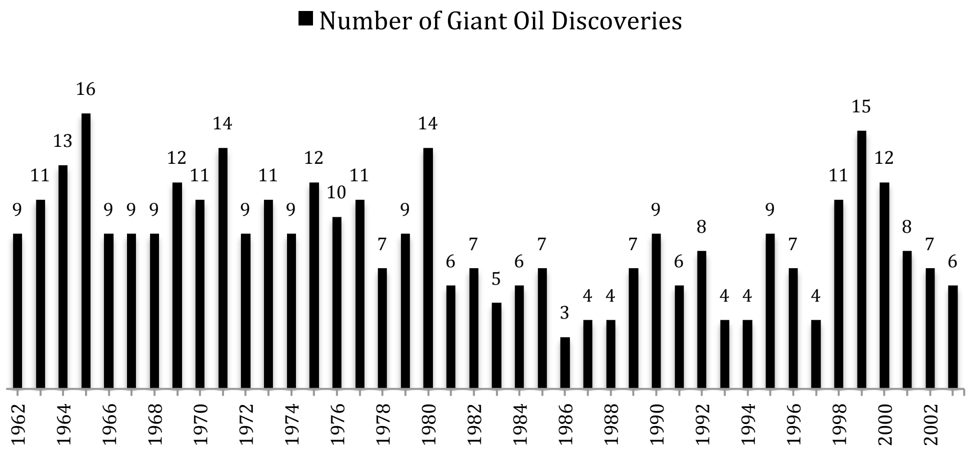


Table 3-2: Number of years (from 1962 to 2003) with one or more giant oilfield discoveries, by country (treatment countries)

Country	Years	Country	Years	Country	Years
Former USSR	29	India	5	Albania	1
Iran	24	Algeria	4	Azerbaijan	1
Saudi Arabia	24	Argentina	4	Bangladesh	1
Australia	18	Colombia	4	Cote d'Ivoire	1
Nigeria	17	Congo, Rep.	4	Denmark	1
China	16	Kuwait	4	Ecuador	1
United States	16	Qatar	4	Equatorial Guinea	1
Norway	15	Peru	3	France	1
Indonesia	14	Thailand	3	Gabon	1
Brazil	13	Tunisia	3	Germany	1
United Arab Emirates	12	Bolivia	2	Hungary	1
United Kingdom	12	Brunei Darussalam	2	Morocco	1
Iraq	11	Italy	2	Namibia	1
Libya	11	Kazakhstan	2	New Zealand	1
Mexico	10	Myanmar	2	Papua New Guinea	1
Egypt, Arab Rep.	8	Netherlands	2	Philippines	1
Oman	8	Pakistan	2	Romania	1
Angola	7	Sudan	2	Russia	1
Canada	7	Trinidad & Tobago	2	Spain	1
Malaysia	6	Vietnam	2	Turkmenistan	1
Venezuela	6	Yemen	2		

3.5.1 Main variables

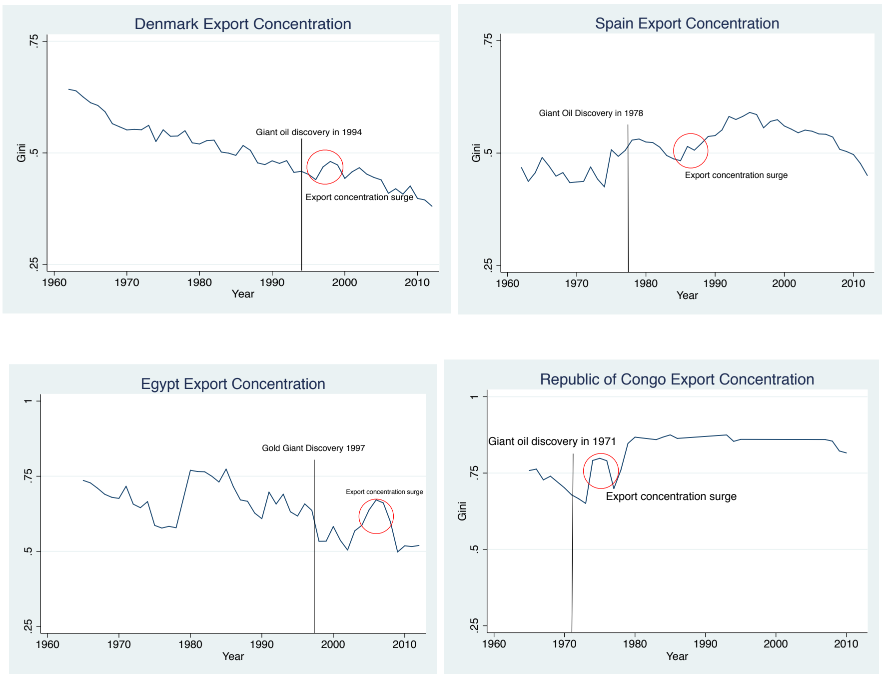
1. Diversification measures: The dataset in this study includes sectoral data on structural change measured by employment, value added and exports. The number of countries in the dataset is 136, ranging between all levels of development. The observations are annual, covering the period from 1962 to 2012. There are many measures for sectoral diversification; most of them are borrowed from the income equality literature. Here we report the Gini index–other indices are available upon request (Theil and Herfindahl-Hirschman). Table B-1 in the appendices presents descriptive statistics of these measures, and table B-2 in the appendices presents the correlation between all the measures, which is rather high. Imbs and Wacziarg (2003) use Gini, HHI and the Coefficient of Variation. Cadot et al. (2011) use Gini and HHI and Moore and Walkes (2010) use only HHI. Lederman and Maloney (2003) use HHI. McMillan and Rodrik (2011) use the Coefficient of Variation. All three measures are calculated in this study, but we report the Gini index only due to the high correlation between the three measures.

From Table B-1 in the appendices, we can observe that the highest diversification in employment (using ILO dataset) happened in Algeria in 1984. The highest export diversification (using WITS dataset) happened in Greece in 2006, while the highest concentration in exports happened in Libya between 1976 and 1981, dominated by the mineral exports sector. Full details on diversification data construction is in Appendix B.

2. Institutional quality measure: The advantages of using the Polity dataset to measure institutional quality is that it covers a broad cross-section of countries throughout our sample in terms of both country and time. Acemoglu et al. (2003) describe Polity measure as “conceptually attractive since it measures institutional and other constraints

that are placed on presidents and dictators" (p. 52). The Polity dataset goes back to independence, and our diversification measures start only from 1962. However, 1962 is a good starting point, as more countries are independent (not colonies), which gives a better reading for their macroeconomic management and also for their Polity scores.

Figure 3-6: Oil discoveries and diversification in exports

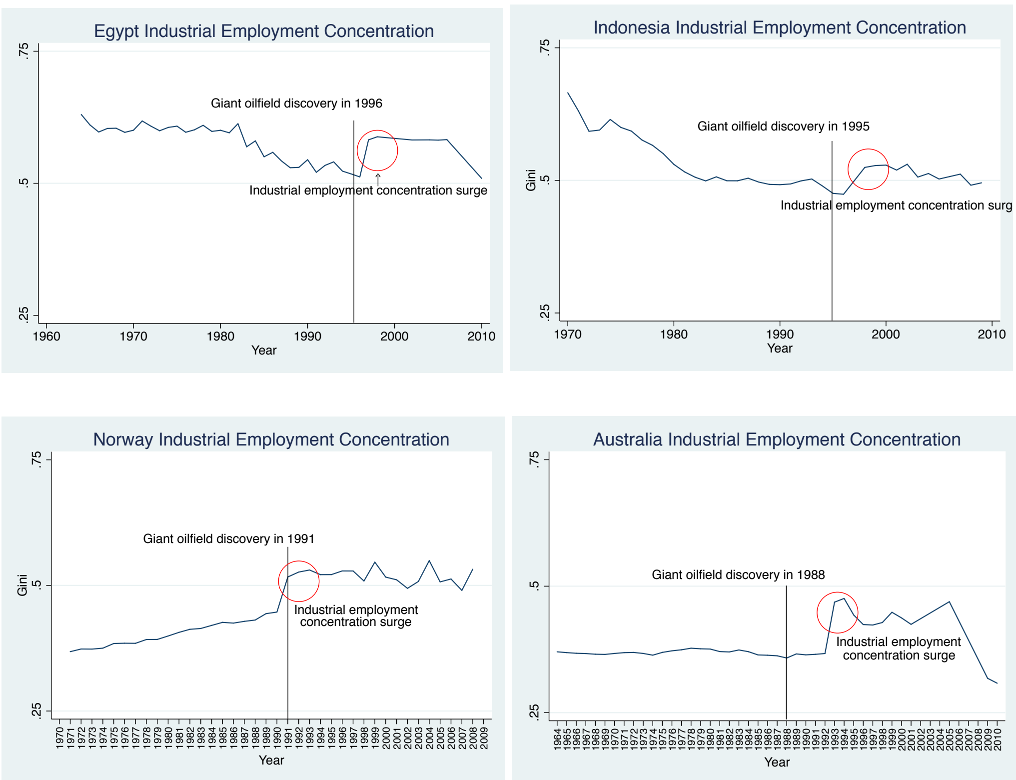


Notes: y-axis shows the Gini coefficient in each country, the x-axis shows the years where data is available. Gini ranges between 0 and 1, where lower Gini indicates higher diversification. The vertical line shows the year of giant oil discovery in each country; the red circle shows the export concentration surge occurring after a giant oil discovery. *Data sources:* Exports data is from WITS. Oil discovery data is from Lei and Michaels (2014).

Figure 3-6 shows that export diversification is affected by giant oilfield discoveries in both democracies (Denmark and Spain) and autocracies (Egypt and the Republic of Congo). The discoveries displayed in these figures are not necessarily exclusive; there might be more giant discoveries in other years.

Figure 3-7 show a surge in employment concentration in democratic governments (Norway and Australia) and autocratic ones (Egypt and Indonesia). Of course, the association between the giant oilfield discoveries and diversification might be coincidental, and among our data there are many discoveries that did not lead to change in diversification. The red circles in both sub-figures show that the surge in concentration following a giant oil discovery is inevitable in both governments: democracies and autocracies. However, in the next sections, we pursue the question of whether giant oil discoveries matter for economic diversification empirically and if it was affected by institutional quality.

Figure 3-7: Oil discoveries and diversification in manufacturing employment



Notes: y-axis shows the Gini coefficient in each country, the x-axis shows the years where data is available. Gini ranges between 0 and 1, where lower Gini indicates higher diversification. The vertical line shows the year of giant oil discovery in each country; the red circle shows the employment concentration surge occurring after a giant oil discovery. *Data sources:* manufacturing employment is from UNIDO. Oil discovery data is from Lei and Michaels (2014).

3.6 Empirical strategy

In order to examine the effect of giant oilfield discoveries on diversification, we begin with a model following Lei and Michaels (2014):

$$\mathrm{Div}_{\mathrm{it+j}} = \beta_{\mathrm{ij}}\mathrm{Disc}_{\mathrm{it}} + \delta \mathrm{X}_{\mathrm{it}} + \alpha_{\mathrm{i}} + \omega_{\mathrm{t}} + \varepsilon_{\mathrm{it}} \,, \qquad (3\text{-}1)$$

where $\mathrm{Div}_{\mathrm{it+j}}$ is the diversification in country i in year t+j, $\mathrm{Disc}_{\mathrm{it}}$ is an indicator for the discovery of a giant oilfield in country i in year t, X_{it} is the number of years with discoveries from t-10 to t-1. α_{i} and ω_{t} are country and year fixed effects, and $\varepsilon_{\mathrm{it}}$ is the error term. To start with, we estimate this specification for different lags j, where j ∈ 2, 4, 6, 8, 10. This allows for examining the impact on the same year of discovery and the following years as well.

For each specification, we present five different timings of the $\mathrm{Disc}_{\mathrm{it}}$ dummy. To ensure that the effects in diversification are not simply caused by temporary changes, we include the timings (t+2, t+4, t+6, t+8, t+10). Moreover, including the future timings is critical for tracking the structural change and export diversification movements over the long run.

Next, we extend the main regression by allowing for the diversification outcomes to depend on the quality of institutions. In order to assess the impact of institutional quality on diversification following a giant oilfield discovery, we rerun equation 3-1 after including the institutional quality covariate, which is an interaction between discoveries and Polity2 score for the year of discovery:

$$\mathrm{Div}_{\mathrm{it+j}} = \beta_{\mathrm{ij}}\mathrm{Disc}_{\mathrm{it}} + \delta \mathrm{X}_{\mathrm{it}} + \gamma \mathrm{Disc}_{\mathrm{it}} * \mathrm{IQ}_{it} + \theta \mathrm{IQ}_{it} + \alpha_{\mathrm{i}} + \omega_{\mathrm{t}} + \varepsilon_{\mathrm{it}}, \qquad (3\text{-}2)$$

where Div_{it+j} is the diversification in country i in years t+j, Disc_{it} is an indicator for the discovery of a giant oilfield in country i in year t, X_{it} is the number of years with discoveries from t-10 to t-1, $\mathrm{Disc}_{it} * \mathrm{IQ}_{it}$ is the interaction term between the giant oil discovery variable and the institutional quality measures, IQ_{it} is the institutional quality measure. α_i and ω_t are country and year fixed effects, and ε_{it} is the error term.

Interaction term = oil discoveries x institutional quality

We compare between these discoveries which happened in a government that received a Polity score less than or equal to zero in the year of discovery, which we will refer to as "autocracies," with those discoveries which happened in a government receiving a Polity score higher than zero, which we will refer to as "democracies." Our main finding is that resource curse applies in countries with grabber-friendly institutions, as well as in countries with producer-friendly institutions, albeit to a lesser extent. These findings add to the resource curse literature in studying the impact of institutional quality on growth, measured by structural change and export diversification, as economic diversification fosters growth in the long run by attracting new economic activity and encouraging transfer of labour from low-paying jobs in low skill-intensive sectors to more productive jobs in high skill-intensive sectors.

3.7 Empirical results

3.7.1 Specification checks

Before testing the impact of giant oilfield discovery on diversification, we test the underlying identification assumption – that giant oilfield discoveries are exogenously timed with respect to underlying economic conditions – by attempting to predict the discoveries using economic variables. To do that, we estimate a fixed-effects logit model, where the independent variables are lags of diversification in different sectors and other economic variables, and the dependent variable is a dummy variable equal to one in the year of a giant oilfield discovery. As shown in Table 3-3, we find that the key variable of interest – diversification – as well as changes in other economic and political variables do not predict giant oil discoveries. We assign changes to differences in two years before discovery to be able to tackle any moves in investments and income that could occur at the beginning or end of the year prior to discovery.

Table 3-3: Do political and economic variables predict giant oil discoveries?

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Previous year's polity2 score	0.005 (0.020)					-.0331 (.0403)				
Previous year's sectoral employment diversification (Gini)		-0.593 (4.017)								
Previous year's manufacturing employment diversification (Gini)			-0.267 (2.278)							
Previous year's growth				-3.58e-14 (9.60e-14)						
4-year lagged oil prices					-.0105 (.0079)	.00402 (.0156)				
Change in income pc							-0.0001 (0.0001)			
Change in government expenditure								-0.0174 (0.228)	-0.0118 (0.0098)	
Change in investments						.0309 (.0216)		0.0359 (0.022)		0.0277 (0.0205)
Observations	2672	772	1437	2092	2130	384	2256	481	1057	481
R^2	0.26	0.25	0.24	0.29	0.24	0.25	0.22	0.24	0.28	0.24

Notes: reported coefficients are from a fixed-effects logit model of the probability of a giant oil discovery occurring in a given year. Standard errors are in parentheses. Columns 5 and 6 show the impact of lagged oil prices on giant oil discoveries–we chose 4-year lag to allow for the time usually taken between exploration and announcement; however, we did not find any shorter lags significant (3, 2, 1 years). The only significant oil price lag is 5-year lag but only at the 10% level; this estimate becomes insignificant if we control for variables in column 6. Any lag more than 5 years becomes insignificant as well. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.7.2 Baseline specification and results

To show how giant oilfield discoveries affect diversification, Table 3-4 shows the results of equation 3-1 before including any institutional quality covariates. The results show that discoveries in a country's recent past have a significant negative impact on export diversification 8-10 years after discovery. This shows that resource countries tend to have more export concentration (mostly in resource exports) with more discoveries. These results suggest that giant oilfield discoveries in a country's recent past have some predictive power for whether a subsequent discovery is likely to be made, as also suggested by Lei and Michaels (2014).

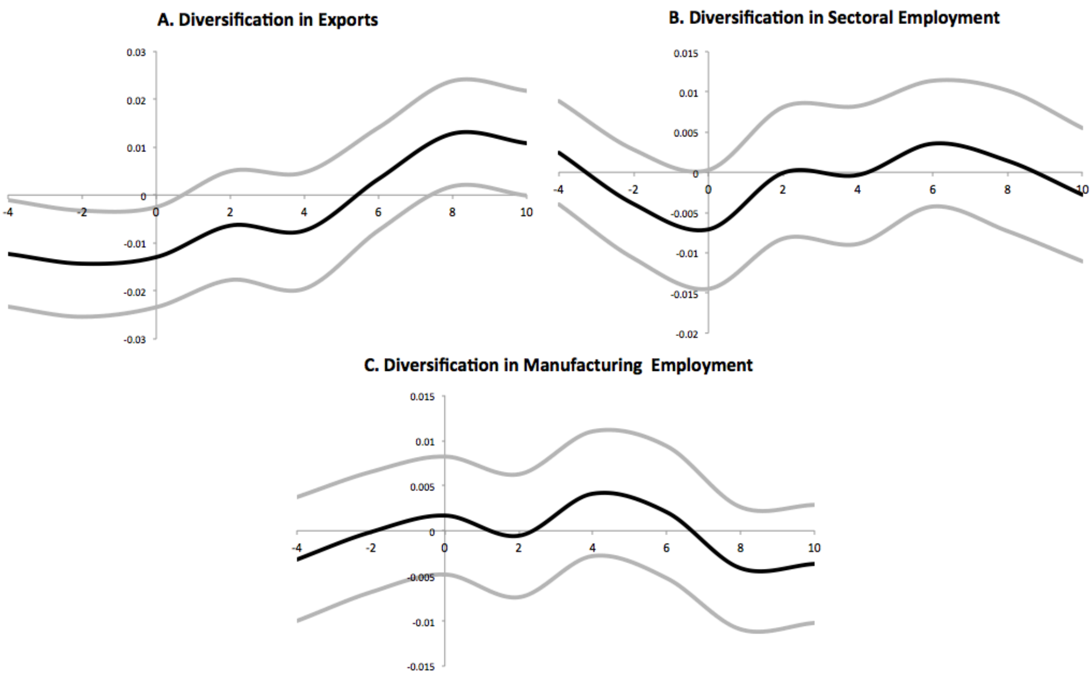
Table 3-4: Effect of giant oilfield discovery on diversification

Outcome in year:	**t+2**	**t+4**	**t+6**	**t+8**	**t+10**
Panel A. Diversification in Exports					
Discovery	-6.36	-7.41	3.35	12.81**	10.81*
	(5.79)	(6.19)	(5.47)	(5.61)	(5.57)
Past discoveries	-6.14***	-5.87***	-7.16***	-8.35***	-8.07***
	(1.52)	(1.50)	(1.45)	(1.56)	(1.51)
Observations	3677	3889	3971	3936	3900
R^2	0.78	0.77	0.77	0.77	0.77
Panel B. Diversification in ILO sectoral employment					
Discovery	-0.07	-0.34	3.57	1.43	-2.79
	(4.17)	(4.37)	(3.99)	(4.46)	(4.23)
Past discoveries	-4.14***	-3.97***	-4.26***	-4.05***	-3.62***
	(0.94)	(0.99)	(0.93)	(1.04)	(0.95)
Observations	2049	2191	2232	2205	2178
R^2	0.84	0.826	0.817	0.814	0.813
Panel C. Diversification in UNIDO manufacturing employment					
Discovery	-0.55	4.11	2.07	-4.15	-3.67
	(3.48)	(3.53)	(3.74)	(3.46)	(3.34)
Past discoveries	0.27	-0.22	0.09	0.85	0.74
	(0.93)	(0.93)	(0.97)	(0.94)	(0.90)
Observations	3120	3244	3289	3263	3235
R^2	0.871	0.868	0.867	0.866	0.866

Notes: Gini index is reported. All regressions control for the number of years with discoveries from t-10 to t-1, and country and year fixed effects. Data sources: (A) export data is from WITS; (B) Sectoral employment is from ILO; and (C) manufacturing employment is from UNIDO. Robust standard errors are in parentheses. All coefficients are multiplied by 1000. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

As a robustness check for these results, Figure 3-8 shows estimates of equation 3-1 for all measures of diversification before and after discovery ranging from t-4 to t+10. All sub-figures suggest that diversification did not change much prior to giant oilfield discoveries. However, responses to discovery vary between sub figures. Sub-figure A shows concentration in exports 8-10 years after discovery, Sub-figure B shows a slight surge in concentration in sectoral employment around 6 years after discovery and fades after that, and Sub-figure C shows a slight surge in concentration in manufacturing employment around 4 years after discovery. By comparing these figures to the results, we can identify the insignificant impacts on diversification that occurred in both sectoral employment and manufacturing employment (Sub-figures B and C). In addition, one might argue that smaller oil discoveries could also have an impact on diversification. To tackle this concern, we examine the relationship between the size of oilfields and diversification. Specifically, we test if non-giant oilfield discoveries could have any impact on diversification. Table B-3 in Appendix B shows that results were mainly insignificant, indicating that major and smaller oil discoveries have no significant impacts on diversification in exports, employment or added value.

Figure 3-8: Impact of giant oilfield discovery on diversification in exports, in sectoral employment, in manufacturing employment and value added



Notes: The x-axes report the number of years before or after t, ranging from t-4 to t+10. The black lines show the estimated coefficients, and the grey lines show the 95% confidence intervals based on robust standard errors, which are clustered by country. All regressions control for previous discoveries (t-1 to t-10) and include country and year fixed effects. Details on variable construction can be found in the data section of the paper.

Another concern is that even giant oilfield discoveries vary in their sizes, so what would happen if the smaller ones among the giant group are also effective? That could raise a question on the usefulness of limiting the data to the giant discoveries only. To investigate this concern, we test the relationship between the different sizes of giant discoveries and diversification. We divide the giant oilfield discoveries by the size of the estimated ultimate recoverable reserves, into four quartiles. In table B-4 in the appendices, we can see that the effect of the smaller three quartiles are mostly insignificant; some are significant only at the 10% level of confidence. However, we find the highest significant negative impact of discoveries in the 4^{th} quartile, which contains the biggest amount of recoverable reserves (quartile 4 ∈ [2733, 160,673]). We find a highly significant negative impact on export diversification around 8 years after discovery.

3.7.3 Diversification and institutional quality

Table 3-5 shows the results of equation 3-2 where we add the institutional quality measures. Based on the resource curse theory, our prediction is that the resource abundance increases concentration in non-tradable sectors, and therefore there is less diversification only when the institutions are grabber friendly. Therefore, we should expect that the interaction term has a negative coefficient. This is what we find in Table 3-5: the interaction term has a positive impact on diversification in all panels. However, the magnitude varies.

The results suggest that the institutional quality measure has significant impacts in most panels, although not all timings, with a persistent positive correlation with diversification. Intuitively, higher Polity2 scores lead to higher diversification after discovery. We will investigate this argument further in the next section. The results suggest a number of main ideas. First, the impact of discoveries on exports' diversification does not change significantly before and after controlling for the institutional quality measure, indicating that all countries tend to get higher concentration in their exports in the long run following a discovery, regardless of their institutional quality. Second, the impact on employment in Panels B and C (sectoral employment and manufacturing employment) was not significant in the baseline specification, but after including the institutional quality covariates we find more significant impact on diversification in the short and long run. The interaction term in Panels B and C is negative, indicating that stronger political institutions would lead to less concentration (higher diversification) in the labour market, following a giant oil discovery. We assume that following a giant oil discovery any concentration in the labour market could be happening in the non-tradable sector, as suggested by the Dutch disease model. Accordingly, better institutions are more concerned about protecting the tradable sector from shrinking; therefore, diversification remains high after a giant oil discovery. However, we will investigate this assumption below.

Table 3-5: Oil discovery, diversification and institutional quality (Polity2)

Outcome in year:	**t+2**	**t+4**	**t+6**	**t+8**	**t+10**
Panel A. Diversification in Exports					
Discovery	-5.10	-6.94	4.82	13.54**	11.03*
	(6.23)	(6.61)	(5.81)	(5.97)	(5.94)
Discovery* Polity2$_{t-1}$	-0.09	0.22	-0.70	-1.21*	-0.83
	(0.68)	(0.72)	(0.66)	(0.62)	(0.66)
Polity2$_{t-1}$	0.02	-0.16	-0.20	-0.15	-0.17
	(0.36)	(0.35)	(0.35)	(0.35)	(0.35)
Past discoveries	-5.66***	-5.08***	-6.16***	-7.29***	-6.98***
	(1.54)	(1.54)	(1.48)	(1.60)	(1.54)
Observations	3500	3703	3781	3746	3710
R^2	0.77	0.77	0.77	0.77	0.77
Panel B. Diversification in ILO sectoral employment					
Discovery	1.02	1.01	7.05	3.24	3.77
	(6.14)	(6.10)	(5.38)	(6.24)	(6.04)
Discovery* Polity2$_{t-1}$	-0.29	-0.36	-0.82	-0.49	-1.26**
	(0.69)	(0.66)	(0.61)	(0.65)	(0.64)
Polity2$_{t-1}$	-3.11***	-3.21***	-3.32***	-3.37***	-3.34***
	(0.22)	(0.22)	(0.22)	(0.23)	(0.23)
Past discoveries	-1.79*	-1.59*	-1.77**	-1.53	-1.13
	(0.92)	(0.96)	(0.90)	(0.98)	(0.92)
Observations	1981	2119	2158	2131	2104
R^2	0.858	0.843	0.835	0.833	0.832
Panel C. Diversification in UNIDO manufacturing employment					
Discovery	1.34	6.05	3.28	-4.57	-3.43
	(3.87)	(3.79)	(4.15)	(3.87)	(3.69)
Discovery* Polity2$_{t-1}$	-1.04**	-1.15***	-0.95**	-0.12	-0.27
	(0.43)	(0.42)	(0.43)	(0.41)	(0.41)
Polity2$_{t-1}$	-1.52***	-1.49***	-1.55***	-1.61***	-1.61***
	(0.20)	(0.20)	(0.20)	(0.20)	(0.20)
Past discoveries	1.14	0.63	1.05	1.84*	1.70*
	(0.93)	(0.93)	(0.98)	(0.95)	(0.92)
Observations	2955	3077	3121	3095	3067
R^2	0.878	0.875	0.873	0.873	0.873

Notes: Gini index is reported. All regressions control for polity2, the number of years with discoveries from t-10 to t-1, and country and year fixed effects. Data sources: (A) exports data is from WITS; (B) Sectoral employment is from ILO; and (C) manufacturing employment is from UNIDO. Robust standard errors are in parentheses. All coefficients are multiplied by 1000 to improve readability. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

One concern is the possibility that the institutional quality measure may be endogenous with respect to natural resources. Ross (2001) addresses this issue and argues that oil countries are not politically weak because of oil per se. He adds that oil rent seeking might have slowed the improvement, but it is not the main reason behind worse institutions. In addition, Sachs and Warner (1995) address this issue and show a weak correlation between institutional quality and resource abundance. This potential endogeneity is not a major concern for the empirical results, as we only address the association between the concerned variables. However, we still take this concern into consideration and we follow Jones and Olken (2004) methodology in observing the Polity2 score in the year prior to the discovery year. This mechanism allows assessing the institutional quality of each government one year before discovery, to avoid any institutional changes that could occur in the same year of discovery as an endogenous effect. Next, we test the impact of another institutional quality measure – constraints on the chief executives. We follow the same approach in tackling the endogeneity concern applied to Polity2 as discussed above. According to Polity IV project, this measure reflects the institutionalised constraints on the power of the decision makers in the government. The measure spans from one to seven, with greater values indicating tighter constraints. Panel A in Table 3-6 shows that the interaction term is negative and becomes significant at the 5% level after eight years of discovery, indicating that stronger political institutions, through limiting executive power, increase the export diversification. Panel B examines the impact on sectoral employment diversification (ILO dataset) and shows stronger impacts. The interaction term is more frequently negative in the long run and becomes significant at the 1% level after 10 years of discovery, indicating that stronger political institutions, through limiting executive power, have a higher impact on employment and structural change than on exports. Panel C did not give consistent results in the case of executive constraints.

Table 3-6: Oil discovery, diversification and institutional quality (executive constraints)

Outcome in year:	**t+2**	**t+4**	**t+6**	**t+8**	**t+10**
Panel A. Diversification in Exports					
Discovery	-4.19	-5.29	1.39	15.09***	11.85**
	(6.15)	(6.73)	(5.84)	(5.82)	(5.91)
Discovery*xconst	-0.42	-0.43	0.55	-0.79**	-0.51
	(0.49)	(0.40)	(0.49)	(0.33)	(0.37)
Executive constraints	0.07	0.03	0.00	0.04	0.02
	(0.11)	(0.11)	(0.10)	(0.11)	(0.11)
Past discoveries	-5.99***	-5.68***	-6.96***	-7.97***	-7.72***
	(1.54)	(1.52)	(1.47)	(1.57)	(1.53)
Observations	3516	3723	3803	3768	3732
R^2	0.77	0.77	0.77	0.77	0.77
Panel B. Diversification in ILO sectoral employment					
Discovery	-2.77	-0.22	25.70**	18.57	23.44**
	(4.25)	(4.47)	(10.95)	(12.13)	(11.37)
Discovery*xconst	0.51**	-0.13	-4.28**	-3.18*	-4.81***
	(0.20)	(0.21)	(1.78)	(1.91)	(1.80)
Executive constraints	-0.38***	-0.40***	-0.42***	-0.44***	-0.44***
	(0.09)	(0.10)	(0.10)	(0.10)	(0.10)
Past discoveries	-3.92***	-3.66***	-3.70***	-3.64***	-3.22***
	(0.95)	(1.00)	(0.94)	(1.03)	(0.96)
Observations	1981	2119	2158	2131	2104
R^2	0.85	0.83	0.82	0.82	0.82
Panel C. Diversification in UNIDO manufacturing employment					
Discovery	-1.27	4.78	0.22	-4.33	-3.42
	(3.69)	(3.72)	(3.89)	(3.71)	(3.74)
Discovery*xconst	0.24	-0.01	0.42*	-0.07	-0.17
	(0.25)	(0.29)	(0.22)	(0.25)	(0.36)
Executive constraints	0.11*	0.11*	0.08	0.12*	0.12*
	(0.06)	(0.06)	(0.06)	(0.07)	(0.07)
Past discoveries	0.48	-0.05	0.41	1.14	1.02
	(0.94)	(0.94)	(0.98)	(0.95)	(0.92)
Observations	2959	3081	3125	3099	3071
R^2	0.88	0.88	0.87	0.87	0.87

Notes: Gini index is reported. All regressions control for polity2, the number of years with discoveries from t-10 to t-1, and country and year fixed effects. Data sources: (A) export data is from WITS; (B) Sectoral employment is from ILO; and (C) manufacturing employment is from UNIDO. Robust standard errors are in parentheses. All coefficients are multiplied by 1000 to improve readability. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

These results suggest that weaker political institutions worsen the impact of oil discoveries on diversification. Producer-friendly institutions may effectively curb rent seeking behaviour, making more resource rents available to improve the non-oil sector, especially the tradables. These findings suggest that oil-rich economies need stronger than usual institutions that are highly monitored with effective checks and balances to contain the potential damage from rent seeking following giant oil discoveries and their anticipated rents. Our empirical findings on the interaction between natural resource dependence and institutions accord with those of Arezki and Gylfason (2013) and Mehlum et al. (2006).

3.7.4 Tradables vs. non-tradables

To foster our understanding of the effect of the interaction between giant oil discoveries and institutions on diversification, it is useful to investigate if the noted high concentration that happens following giant discoveries falls in the tradable or the non-tradable sectors. We explore this question in Table 3-7, by examining how giant oil discoveries and their interaction with the Polity2 score affect the likelihood of employment in tradable versus non-tradable sectors as an outcome variable, instead of the diversification measures reported earlier.

Table 3-7: Giant oil discoveries and the share of non-tradable to tradable sector employment

Dependent variable: *relative share of employment in non-tradable to tradable sectors*					
	t+2	**t+4**	**t+6**	**t+8**	**t+10**
Discovery	0.029**	0.015	0.001	-0.003	-0.018
	(0.014)	(0.015)	(0.015)	(0.015)	(0.016)
Discovery*polity2	-0.002	-0.002	-0.004**	-0.004**	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Polity2	-0.006***	-0.005***	-0.005***	-0.005***	-0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Past discoveries	-0.007	-0.006	-0.004	-0.003	-0.003
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Observations	1993	2136	2181	2158	2136
$\mathbf{R^2}$	0.89	0.89	0.89	0.89	0.89

Notes: From the ILO dataset (ISIC-revision 3), we identify five sectors to be tradable sectors: 1. Agriculture, hunting, forestry and fishing; 2. Mining and quarrying; 3. Manufacturing; 4. Electricity, gas and water supply; and 6. Wholesale and retail trade, restaurants and hotels, repair of motor vehicles. The remaining four sectors are non-tradable: 5. Construction; 7. Transport, storage and communication; 8. Financing, insurance real estate and business services; 9. Community, social and personal services. This classification between tradable and non-tradable sectors is based on the European Commission Annual Macro-Economic Database (AMECO). Standard errors are in parentheses. All regressions control for polity2, the number of years with discoveries from t-10 to t-1, and country and year fixed effects.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

In Table 3-7, we provide evidence supporting our argument by documenting that giant oil discoveries lead to higher (lower) employment share in the non-tradable sectors compared to tradable sectors in countries with lower (higher) Polity2 scores. Intuitively, countries with more grabber-friendly institutions tend to suffer more from the Dutch disease as more new jobs are created in the non-tradable sector compared to the tradable sector. That might have been caused by higher demand in the services and other non-tradable sectors, which emphasises the resource movement effect following a resource boom. These results accord with the Dutch disease dynamics suggested by Van der Ploeg and Venables (2013), who argue that structural change happens in the economy following a resource discovery.

3.8 Conclusion

This paper estimates the causal impact of natural resources in different sets of institutional quality on the existence of a resource curse, measured by diversification indicators in exports and employment. We find that countries respond differently to giant oil discoveries, as we aim to show if the quality of institutions determines whether countries avoid resource curse or not. The combination of grabber-friendly institutions and giant oil discoveries leads to a less diversified economy in non-tradable sectors, whereas producer-friendly institutions help countries to take full advantage of these discoveries and the following revenues, and maintain the employment share in the manufacturing sector and tradables. However, we find little evidence that producer-friendly institutions help countries to avoid export concentration, as all countries tend to have concentrated exports with large shares in the resource sector.

Results indicate that the manufacturing sector is the most negatively affected sector. More labour movements out of the tradable sector could have a negative impact on growth in the long run, which might be a single step towards the spending effect of the Dutch disease. It is possible that the final impact would take a longer time to stabilise than is studied here.

It is, however, challenging even for countries with good institutions to maintain labour in the manufacturing sector, being crowded out in exports' share. Norway's resource exports reached almost 50% of total exports in 2013, crowding out other tradables, as manufactures' share in exports dropped from almost 70% in 1972 to only 17% in 2013. The shares per se should not be a concern, but the association with less non-resource output should be alarming, calling for further enhancements in supporting producer-friendly institutions in these countries, as the good performance may not last for long.

These results add to the Dutch disease main theory when gas production negatively affected the manufacturing sector even in countries with good institutions, such as the Netherlands.

The question remains: Why is relatively better performance in resource countries associated with better institutional quality? This could give room for more future research to investigate different institutional quality measures and the specific types of regulations that support producer friendly institutions.

Chapter 4

Oil Booms, Dutch Disease and Manufacturing Growth

4.1 Introduction

Oil and gas production has affected producer countries worldwide, and many countries have been affected both positively and negatively by the booms and busts of the past 40 years. A major question in front of governments is the impact on the manufacturing sector, as many countries rely on trading manufactured products – a lot more than they do on services – for long-term growth and productivity. If the tradable sector is negatively affected, governments begin to get concerned about the potential "Dutch Disease," which is a widely-used term in the development literature as a leading mechanism for a "Natural Resource Curse." The Economist magazine coined the term in 1977 to explain the gas boom implications on the Dutch economy. The "resource curse" was first noted by Sachs and Warner (1995, 2001), who show a significant negative relationship between natural resource dependence and growth in GDP per capita. They also argue that resource abundance squeezes the manufacturing sector, as in the Dutch disease model. Other studies considered oil rents specifically and find a negative relation between oil rents and economic performance (Sala-i-Martin & Subramanian, 2003).

The extensive literature on the Dutch disease (Krugman, 1987; Van Wijnbergen, 1984; Van der Ploeg & Venables, 2013) is pioneered by Corden and Neary (1982), who show a decline in manufacturing employment and exports as a result of resource boom. Three factors can cause this boom: a technology-induced rise in productivity, a new resource discovery, or a rise in the commodity world price. In this paper, we are able to cover two of these factors in our empirical strategy: a new resource discovery, and the rise (and fall) of the commodity world price. Corden and Neary (1982) distinguish between two main effects of the resource boom on the manufacturing sector; the *spending effect* occurs when a sudden rise in the value of the natural resource exports raises real income leading to extra spending on services, which raises export prices and leads to adjustments in real exchange rate. That makes exporting non-resource commodities more difficult, and makes competing with imports across a wide range of commodities harder. Foreign exchange earned from the resource exports may be used to purchase internationally traded goods, at the expense of domestic manufacturers of the goods. Simultaneously, domestic resources such as labour and materials shift to the resource sector, where the *resource movement effect* takes place. Consequently, the prices of these resources rise in the domestic market, thereby increasing the costs to producers in other sectors. Eventually, extraction of natural resources sets in motion a dynamic that gives primacy to two domestic sectors – the natural resource sector and the non-tradable sector, at the expense of more traditional export sectors.

Higher resource revenues accompanied by more income tax revenues might increase governments' ability to support the harmed manufacturing sector by better infrastructure and policies that raise productivity (Michaels, 2011). On the other hand, higher income might have a stronger impact through the spending effect, leading labour to move out from the tradable manufacturing sector that is facing high competitive pressure to industries that meet the high local demand, mainly services and non-tradable manufacturing. Thus, even accepting the core model, the question of how a resource boom affects the tradable sector is ultimately an empirical one. For example, Forsyth and Kay (1981) argue that the manufacturing output in the UK fell in the 1970s as the UK started to produce oil at that time. They observed that manufacturing output has fallen in the UK by 10%, whereas it grew in Germany by 10%, and the two are comparable industrial countries. They argue that the difference in the UK comes from the increase in real national income, depressing the share of manufacturing and probably increasing the share of local industries to meet the local increasing demand.

In this paper, we estimate the causal effect of two commodity shocks suggested by the Dutch disease hypothesis on the tradable manufacturing sector: giant oil discoveries as a resource discovery shock, and oil price boom and bust as a commodity price shock. Using panel analysis, we compare between countries that have discovered giant oilfields to countries that have not during 1962-2012. The methodology is adapted from Rajan and Subramanian (2011), which evaluates the impact of receiving foreign aid on the tradable manufacturing sector. We follow Rajan and Subramanian (2011) in using the dataset provided by the United Nations Industrial Development Organization (UNIDO): the industrial statistics database, which is derived largely from industrial surveys. We also follow their exportability classification in assigning certain manufacturing industries as “exportable” and focusing on them to assess the impact on the tradable industries within the manufacturing sector.

Oil discoveries will probably lead to higher oil revenues and hence local currency appreciation. This appreciation would likely affect local manufacturing firms through three different channels (Ekholm et al., 2012): first, through the firm’s export sales that would be harmed by competitiveness. Second, through the firm’s purchases in imported inputs that would get cheaper. Third, through import competition facing the firm in the domestic market, as imports get cheaper. Rajan and Subramanian's (2011) paper is based exclusively on poor and developing countries that receive aid. Therefore, their exportability index is based on labour-intensive industries that fit best within these countries. Since our data has a wider coverage and includes oil discoveries in the developed countries as well, we construct another exportability index, based on the same methodology of Rajan and Subramanian (2011), but which fits more the manufacturing exports in developed countries, which are usually more capital-intensive. We find it very useful to include the capital-intensive export index, as manufacturing has become more technological recently, and using both indices together. Rodrik (2013) argues that there are technological changes in manufacturing itself that have made the sector much more capital- and skill- intensive than in the past, reducing both the advantage of poor economies in manufacturing and the scope for labour absorption in the sector. We look into the heterogeneity between the two indices on three manufacturing outcomes provided by the UNIDO dataset: value added, wages and employment. We chose to expand our outcomes and not only focus on value added as in Rajan and Subramanian (2011), in order to be able to track spillovers within the manufacturing sector itself. Additionally, Allcott and Keniston (2014) suggest that the impact of resource booms on manufacturing depends on three factors: if local manufacturing wages rise, if manufacturing is traded or not, and if there are local productivity spillovers from resources to manufacturing. We are able to test all of these channels in this paper, with more focus on the tradable industries within manufacturing.

A major concern in our design is whether oil discoveries are exogenous or not. We test if related economic and political factors could predict discoveries and we do not find any significant impacts, proving the exogeneity of giant oil discoveries. In addition to the economic and political variables tested in this paper, one might also argue that governments or other entities could manipulate the exact timing of the announcement of a giant oil discovery. Arezki et al. (2015b) argue that this is not plausible in Mike Horn's dataset that we use in this paper, as Horn shows that these concerns about a possible manipulation have little ground. In addition, they also argue that Mike Horn's dataset is immune from such concerns, "*as each discovery date included in his dataset has been independently verified and documented using multiple sources which are reported systematically for each discovery date*" (p.15). We also address the issue of the possibility that past discoveries could predict future discoveries. Arezki et al. (2015b) show that previous oil discoveries could have two opposite impacts on the possibility of current and future discoveries. First, more discoveries could increase discovery costs, reducing the likelihood of future discoveries. Second, and on the other hand, previous discoveries enhance learning about the geology and therefore increase the chances of future discoveries. Accordingly, previous discoveries could have any of the noted two impacts. To control for this uncertainty and for the serial correlation that could arise between discoveries, we include the number of giant discoveries in each country from t-10 to t-1 for each discovery in year *t*, in addition to the industry, country and year fixed effects in our empirical design.

Our second commodity shock, the oil prices boom and bust, is described by Bjørnland and Thorsrud (2016) as a major exogenous element that could potentially affect all sectors of the economy. We argue that oil price is an exogenous shock because it is driven by international prices that cannot be controlled by a single country, having in mind that the oil market in both the demand side and supply side is quite big. In this paper, we will only consider oil price shocks rather than all commodities, as it is the main variable in our identification.

The literature focuses on two possible channels affecting manufacturing growth (Buera & Kaboski, 2009; Foellmi & Zweimüller, 2008, Ngai & Pissarides, 2004): first, demand-based reasons which rely on a shift in consumption preferences away from goods towards services; second, technological reasons that rely more on rapid productivity growth in manufacturing than in the rest of the economy. However, Matsuyama (2009) finds that the effects of technology and demand shocks depend crucially on whether the economy is open to trade or not. Hence, our empirical strategy tests if openness to trade could influence the impact of resource booms on manufacturing. We test for this impact to examine if higher government revenues lead to better policies that support the tradable manufacturing sector, as suggested by Michaels (2011).

We find a significant negative impact of oil discoveries on the manufacturing sector. The concern appears if employment is declining in the manufacturing sector and instead moving into the non-tradable sector for a number of reasons (Rodrik, 2013). The most important feature of manufacturing employment is that much of it is labour-intensive, so it can absorb large amounts of relatively unskilled workers from the rest of the economy, especially in the developing countries. Harming manufacturing jobs while increasing resource dependency should be alarming for these countries.

This paper contributes to the literature in the following ways. First, to our knowledge, it is the first paper to test the causal impact of exogenous measures of natural resource booms on the manufacturing sector in that large a scale in time and scope. The paper provides a comprehensive analysis of the relationship between resource booms and activity at the manufacturing industry level in resource-rich economies. Second, our data covers both developing and developed countries provided by the UNIDO dataset, where previous papers covered only one country group, or a single country. Third, most of the literature analysing the benefits and costs of resource booms on manufacturing has been theoretical, and there are relatively only few empirical studies (Bjørnland & Thorsrud, 2016). The standard Dutch disease model in many of these papers does not account for productivity spillovers between the oil sector and the rest of the economy, through analysing the impact on total manufacturing.

To address these issues with empirical evidence, we also test the effects on the tradable manufacturing industries. Other manufacturing industries could be growing to meet increasing local demand, as suggested by the literature, and thus could give misleading results to the Dutch disease hypothesis. To answer this question, we identify two structural shocks: resource boom shock, and commodity price shock. To the best of our knowledge, this is the first paper to separate and quantify these two channels on a long panel on an industry level basis.

The rest of this paper proceeds as follows: the following section views related papers on oil discoveries, structural change and manufacturing growth. Section 3 provides a brief background and statistics on the two resource shocks used in this paper – oil discoveries and oil price shocks. Section 4 outlines our empirical strategy. Section 5 presents the main results and discussions. Section 6 concludes.

4.2 Related literature

The theoretical literature on Dutch disease has been far more developed than the empirical literature. Most recent empirical studies test common movements in manufacturing across countries where they find that the impact of resource booms on manufacturing is limited, if not positive. However, none of these papers accounted for manufacturing at the industry level and none of them highlighted the impact on the tradable industries, which are most related to the Dutch disease hypothesis. The empirical strategy in this paper accounts for that.

Ismail (2010) uses sectoral data for manufacturing across oil exporting countries and finds that oil price shocks depress value added across manufacturing in countries with more open capital markets. Arezki and Ismail (2013) test the Dutch disease on a sample of 32 oil-rich countries from 1992 to 2009 and find that during an oil boom, fiscal policies have helped to reduce capital expenditure. Harding and Venables (2013) find that exports of natural resources crowd out non-resource exports. They claim that the impact on non-resource exports becomes greater in countries with high income and good governance, as these countries tend to have a higher manufacturing share in their non-resource exports.

More recently, Allcott and Keniston (2014) investigate the impact of oil and gas discoveries on manufacturing in the United States. They argue that resource booms boost growth by increasing total employment and wages. They also suggest that manufacturing employment, output and productivity are all pro-cyclical with resource booms. They argue that these results challenge the argument that natural resource extraction is unlikely to drive growth.

Bjørnland and Thorsrud (2016) study productivity spillovers between the booming resource sector and other domestic sectors, and find that Norway and Australia (two resource-rich countries) are facing a two-speed economy where services and non-tradables are growing at a much faster pace than manufacturing and tradables. They find that resource booms have significant and positive productivity spillovers on non-resource non-tradable sectors in both countries. They also find some differences between the two countries' performance after discovery, depending on the resource dependency level and the real exchange rate fluctuation. They argue that increased activity in the technologically intense service sectors and the boost in government spending derived by changes in the commodity price had a positive impact on value added and employment in the Norwegian economy, while the Australian economy captures the full effect of the Dutch disease and manufacturing declines. Rajan and Subramanian (2011) test aid rather than resources as the windfall and find that aid inflows have systematic adverse effects on a country's competitiveness, reflected in the lower relative growth rate of tradable industries, measured by the growth in manufacturing value added. Accordingly, even aid inflows do cause Dutch disease.

A few recent papers have included oil discoveries into their specifications aiming to study the resource curse. Lei and Michaels (2014) find that giant oilfield discoveries can lead to armed conflict. They use giant oil discoveries as a measure for natural resources, as they argue it is exogenous and could give more reliable results. A related paper with a different outcome is Cotet and Tsui (2013), where they use discoveries of all sizes and find no relationship between oil wealth and civil war. They agree with Lei and Michaels (2014) by arguing that the fixed effects model does not estimate the causal effect of oil on civil war, because oil exploration might be endogenous in that case. To handle this problem, they extend the analysis to instrument oil wealth by natural disasters and proven oil reserves. Arezki et al. (2015b) follow Lei and Michaels (2014) by restricting the oilfield discoveries to the giant ones. They claim that giant oil discoveries provide “a unique source of macro-relevant news shocks” (p.3), as they test the impact of oil discoveries on a number of macroeconomic outcomes using ARDL model. Arezki et al. (2015a) study the discoveries’ impact on conflict, Arezki et al. (2015b) study the impact on macroeconomic outcomes, and Smith (2015) studies the impact on GDP growth.

In the literature investigating productivity growth and structural change, McMillan and Rodrik (2011) argue that there are large productivity gaps between different parts of the economy in developing countries and between different firms within the same part or industry. These gaps are smaller in developed countries. They acknowledge that structural change could move in different directions along with the economic development process. In resource-rich countries in particular, natural resources do not generate much employment compared to manufacturing and other tradable sectors, which takes structural change in a direction away from productive sectors. In Africa and Latin America, for example, manufacturing and some other modern sectors have lost employment to lower productivity services and informal activities.

Rodrik (2012) argues that too much of an economy’s resources can get stuck in the ‘‘wrong’’ sectors – those that are in the informal sector. Even if resource-rich countries are doing well in terms of growth coming from the informal or from the non-tradable services sectors, manufacturing tradables could still be an important phase in these countries’ growth path, especially if these countries still have a significant portion of unskilled labour that might not be working in a high-productivity high-skill service industry or even a tech-based manufacturing industry. He adds that natural resource booms can definitely fuel growth, but could also come with many problems: capital-intensity, low labour absorption, and the politics of rents.

Some recent papers examine the growth in the manufacturing sector. Diao and McMillan (2015) study the overall African economy including both formal and informal sectors and find that the share of manufacturing exports in total exports is actually growing, and not primarily depending on natural resource exports. This increase was driven by a range of manufactured exports varying from labour-intensive activities, like textile and shoe manufacturing, to capital-intensive activities such as oil refining. Between 2000 and 2010, the share of manufacturing exports in goods and services more than doubled from 10% to 23%. They argue that it is more useful to classify modern economic activities in Africa based on the exportability, as manufacturing could be in both formal and informal sectors, while the informal sector is growing rapidly in Africa and employment rates are increasing there. We take this classification into consideration in our paper. They add that the informal sector is less dependent on globalisation where productivity is low, while productivity is high in the formal sector as it is more related to international companies operating across borders. On the contrary, Rodrik (2016) finds that the manufacturing share in both employment and real value added has been falling in developing countries since the 1980s, with some exceptions in Asia. Manufacturing typically follows an inverted U-shaped path over the course of development, but it usually falls if the country does not have a comparative advantage.

On the impact of real exchange rate appreciation on local economies, Kenen and Rodrik (1986) argue that the experience with real exchange volatility has differed greatly across countries. Plus, this volatility depresses the volume of international trade. Chatterjee et al. (2013) find that if real exchange rate appreciates, firms expand their product scope so their sales distribution across different products becomes less skewed in response to real exchange rate depreciation. Ekholm et al. (2012) argue that the extent to which a real exchange rate shock changes the competitive pressure on a firm is determined by its exposure to trade. Real exchange rate appreciation shock led to less employment in exportable industries in Norway but a rise in productivity (and output) due to within-firm improvements or cheaper imported inputs. The fiercer international competition resulting from real exchange rate appreciation may affect manufacturing employment by forcing restructuring in surviving firms, or triggering the exit of less profitable firms, both increasing productivity (output per worker). The paper also argues that productivity was not affected in sectors that experienced high import competition; instead, it increased in more exportable industries. Fung (2008) finds that the expansion of scale of continuing firms induced by real exchange rate appreciation contributes significantly to productivity growth at the firm level through exploiting economies of scale. As some firms faced by real exchange rate appreciation shock exit the market, the continuing firms gain a larger market share and their productivity increases.

Although recent papers on natural resources have provided more convincing empirical designs and models, the issue of endogeneity is still very plausible. We argue that the approach we follow in this paper is most likely to be exogenous, for several reasons. First, the fixed effects model controls for any differences in the main characteristics before and after the giant oil discoveries. Second, as we show in the next section, none of the main country characteristics could predict giant oil discoveries. Third, we argue that the oil price shock is completely exogenous, as the prices are international and the market contains a large number of countries in both the demand and supply sides. Finally, the empirical design controls for time-invariant factors present before and after discovery.

To sum up, the related literature suggests that if the exportable manufacturing sector in resource-rich countries is declining, as we find in this paper, while overall growth is increasing (e.g., Allcott & Keniston, 2014, Smith, 2015), this would mean that growth in resource-rich countries is driven by growth in the informal sector (Diao & McMillan, 2015), which grows through increasing local demand enhanced by the spending effect, and does not have a significant share in exports nor gets affected by globalisation (Rodrik, 2016).

4.3 Oil discoveries and oil price shocks

Oil discoveries:

We use a dataset on oil discovery from Lei and Michaels (2014), which is based on a dataset by Horn (2003, 2004). Horn reports the date of discovery, the name of the discovering country, and a number of other variables, for 910 giant oilfields discovered both onshore and offshore from 1868 to 2003. To qualify as a giant, an oilfield must have contained ultimate recoverable reserves of at least 500 million barrels of oil equivalent. To avoid measurement error, Lei and Michaels (2014) constructed an indicator for whether a country is mentioned in the dataset as having discovered at least one giant oilfield in each given year.

Table 4-1 shows that discoveries peaked in the 1960s and 1970s, but double-digit number of oilfield discoveries returned in the late 1990s. Of the 910 giant oilfields covered in Horn (2004), and 782 covered in Lei and Michaels (2014), 364 are used in this paper to cover the period 1962-2003. This limitation is due to the data availability offered by UNIDO, where the earliest data available is 1962. However, our data on manufacturing continues up to 2012 to assess the impacts of discoveries that occurred during the 2000s in the long run, which is 8 to 10 years after discovery, as we show in some results.

Table 4-1: Number of one or more giant oilfield discoveries (from 1962 to 2003), by year

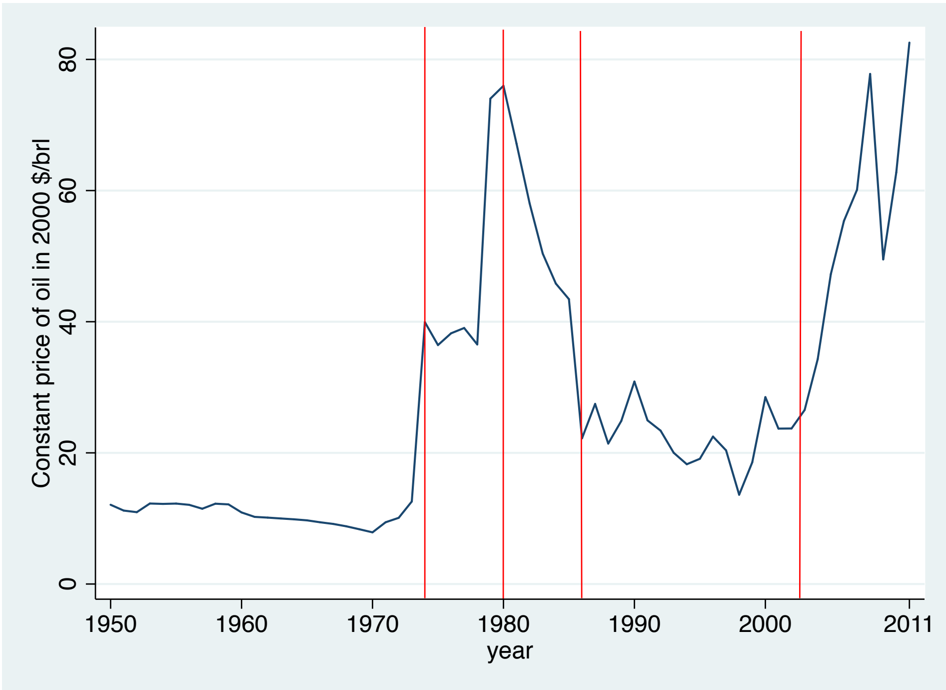
Year	Number of giant oilfield discoveries	Year	Number of giant oilfield discoveries	Year	Number of giant oilfield discoveries	Year	Number of giant oilfield discoveries	Year	Number of giant oilfield discoveries
1962	9	1971	14	1980	14	1989	7	1998	11
1963	11	1972	9	1981	6	1990	9	1999	15
1964	13	1973	11	1982	7	1991	6	2000	12
1965	16	1974	9	1983	5	1992	8	2001	8
1966	9	1975	12	1984	6	1993	4	2002	7
1967	9	1976	10	1985	7	1994	4	2003	6
1968	9	1977	11	1986	3	1995	9		
1969	12	1978	7	1987	4	1996	7		
1970	11	1979	9	1988	4	1997	4		

The data contains 364 country-year observations, with giant discoveries accounting for 5.2% of total observations. Table 4-2 shows that giant oilfield discoveries are rare events in most countries, and country-year pairs with discoveries were most common in Asia (40%), followed by Africa (17%), Europe (19%), South America (10%), North America (9%) and Oceania (5%). The treatment group is countries that have had at least one giant oil discovery during the study, which consists of 64 countries, whereas the control group is the countries that have never had any giant oil discoveries during that time, which consists of 72 countries, providing a balanced comparison.

Oil price shocks:

The most significant oil price shocks took place in the 1970s when the Arab oil exporting countries declared an oil embargo in response to the Western support for Israel against Syria and Egypt at that time. Oil prices quadrupled between 1973 and 1974, and remained high for several years. Prices hiked again in 1979 in response to the Iranian revolution. In 1981, oil prices crashed for a number of reasons; most significantly was oversupply, increase in demand for alternative energy sources and declining economic activity in developed countries. Prices remained relatively low until the mid-2000s. Figure 4-1 shows a graph of oil prices in real U.S. dollars from 1950 to 2011, with vertical lines representing the boom and bust periods.

Figure 4-1: Oil price boom and bust periods 1950-2012



Notes: Oil prices are constant prices of oil in 2000. Red lines represent oil price shocks, oil booms from 1974-1980 and 2002-2012, bust from 1981-1986, and valley from 1987-2001. Data source: M. Ross, Oil and Gas Data, 1932-2011, Harvard Dataverse Network, 2013 provided by the QOG Basic Dataset 2015 (Teorell et al., 2015).

We identify the boom and bust periods following the literature[15]. The boom periods are the years between 1974-1980 (boom1) and the years between 2002-2012 (boom2)[16], and the bust period is the years between 1981-1986; we also add the "valley" period between the years 1989-1995. The data we use for oil prices is taken from the QOG Basic Dataset (Teorell et al., 2015).

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15 As mentioned in the introduction, we follow several papers by Hamilton (1983, 2009, 2011) among others (e.g., Kilian, 2008; Smith, 2014).

16 We also break up the 2000s boom into two booms: boom3 between 2002-2007 and boom4 between 2009-2012. This is to account for the oil drop in 2008. Results show same direction and are reported in Table C-5 in appendix C.

4.4 Empirical strategy

We use the following equation to assess the impact of giant oil discoveries on several outcomes, following Rajan and Subramanian (2011):

$$\Delta \ln(Y_{cit}) = \beta_1(Disc_{ct} * Exportability_{ci}) + \beta_2 X_{ct} + \beta_3 Industry_{cit-1} + \gamma_i + \alpha_c + \omega_t + \varepsilon_{cit} \quad (4\text{-}1)$$

where Y_{cit} is the outcome of interest for industry i in country c in year t. Disc_{it} is an indicator for the discovery of a giant oilfield in country c in year t. Exportability index is a dummy that takes on a value of 1 for exportable ISIC industries and 0 otherwise[17]. X_{ct} is the number of years with discoveries in country c from t-10 to t-1. $Industry_{cit-1}$ is the share of industry i in country c as a share of total manufacturing sector analysed outcome one year prior to discovery (t-1). This is included to control for the possibility of convergence effects. γ_i is industry fixed effects, α_c and ω_t are country and year fixed effects, and ε_{cit} is the error term. β_1 is our main interest.

The data for industry value added, employment and wages comes from the Industrial Statistics database (2015) of the United Nations Industrial Development Organization (UNIDO) (INDSTAT2, 2013) series covering the years 1962-2012. The data is at the 2-digit level of the International Standard Industrial Classification of All Economic Activities (ISIC, Revision 3) and has been available since 1962. This dataset offers a number of advantages and disadvantages. The major advantage for the INDSTAT2 data is the good coverage of countries going back to the early 1960s for up to 23 manufacturing industries per country, and it is the largest industrial statistics database of

[17] Rajan and Subramanian (2011) provide a detailed description of exportability indices: exportability index 1 is described as a "dummy that takes a value of 1 if industry i has a ratio of exports to value that exceeds the industry median value. For each industry, the average ratio of exports to value added was calculated using a group of developing countries". Exportability index 2 is a dummy for industries (ISIC 321-324); we follow their strategy and build another exportability index instead of that, but depending on industries (ISIC 29-35). For full industry description please see Table C-2 in appendix C.

its kind[18]. Some papers in the literature use INDSTAT4 instead, as it provides more disaggregated data at the four-digit level for up to 127 industries, but on the other hand, it covers fewer countries, fewer years and is patchy for earlier years, making it impractical to work with for periods that extend before 1990. In this paper, we follow Rodrik (2013) by using INDSTAT2, which has the advantage of allowing us to increase the country coverage as well as present results for periods earlier than 1990. Yet we also use INDSTAT4 for robustness tests. We use INDSTAT2 to build the exportability indices 1 and 2, through matching the industries with the ones selected by Rajan and Subramanian (2011) for index 1-developing countries, and by choosing ISIC industries 15-26 for index 2-developed countries, as shown in Table C-2 in the appendices.

We should note that our data provided by UNIDO does not cover any activities in the informal sector and microenterprises, which are often excluded from such industrial surveys. We cannot be certain that the results are applicable to all types of manufacturing activities, and therefore we only claim that our findings are applied to the organised formal parts of manufacturing.

Our main measure of manufacturing is the annual growth in value added, following Rajan and Subramanian (2011). In addition, Rodrik (2016) finds value added a better measure of manufacturing than employment share of manufacturing. Data of value added is provided in current U.S. dollars. We deflate these values using the US Producer Price Index from the International Financial Statistics to get real values.

In this paper, we are not addressing the impact of resource booms on local demand or manufacturing for local consumption. We entirely focus on the tradable manufacturing industries. Our assumption is that if the real exchange rate appreciates in resource

[18] As described by UNIDO: https://www.unido.org/resources/statistics/statistical-databases.html

countries caused by resource discoveries, their export competitiveness could decline. Therefore, we first test the effect of giant oil discoveries on the real exchange rate. Then we further analyse this impact by testing if real exchange rate appreciation (or depreciation) caused by giant oil discoveries has an impact on the exportability, by using the following equation:

$$\Delta \ln(Y_{cit}) = \beta_1(RER_{ct} * Exportability_{ci}) + \beta_2(Disc_{ct} * Exportability_{ci}) + \beta_3 X_{ct} + \beta_4 Industry_{cit-1} + \gamma_i + \alpha_c + \omega_t + \varepsilon_{cit} \quad (4\text{-}2)$$

Equation 4-2 is similar to equation 4-1 – we only add the real exchange rate appreciation measure RER_{ct} to assess the impact of giant oil discoveries and the real exchange rate appreciation on the manufacturing value added within the tradable industries in oil countries Y_{cit}. We follow Rodrik (2008) in calculating the real exchange rate appreciation measure, which is the logged deviation of the actual price level from the estimated price level using data from PWT 8.0.

Next, we test the role of the country's openness to trade in our model. These two steps are taken to be able to see if globalisation and openness have any role in this structural change, following Rajan and Subramanian (2011) and Bjørnland and Thorsrud (2016). Hypothetically, we are assuming that if real exchange rate appreciates after a giant oil discovery – caused by real revenues from oil exports in the medium term – the tradables should become more expensive in the international market compared to similar products from other non-oil countries. The competition will lead to less demand for the oil country's tradables and eventually the tradables' production will decline. In addition, if the country is more open to international trade, it should be more vulnerable to exogenous shocks affecting its own exports. For this assessment, we replace the real appreciation variable in equation 4-2 by the openness variable, taken from the PWT dataset.

After that, we test the second exogenous resource shock in our strategy by using the boom and bust as a test of a price-driven resource shocks. We use the following equation to assess that impact:

$$\Delta \ln(Y_{cit}) = \beta_1(Boom_t * Exportability_{ci}) + \beta_2(Bust_t * Exportability_{ci}) + \beta_3(Valley_t * Exportability_{ci}) + \beta_4 Industry_{cit-2} + \gamma_i + \alpha_c + \omega_t + \varepsilon_{cit} \qquad (4\text{-}3)$$

where Y_{cit} is the outcome of interest for industry i in country c in year t. $Boom_t$ is an indicator for being between the years 1974-1980 or between 2002-2012, $Bust_t$ is an indicator for being between the years 1981 and 1986, and $Valley_t$ is an indicator for being between the years 1987 and 1995. Therefor, β_1 is the average difference in outcome growth rates in exportable sectors (indices 1 and 2) between treatment and control countries during the boom period, conditional on country, year and industry fixed effects. β_2 and β_3 have the same interpretation for the bust and valley periods. Similar to equation 4-1, $Industry_{cit-2}$ is the share of industry i in country c as a share of total manufacturing sector analysed outcome two years prior to discovery (t-2). This is included to control for the possibility of any convergence effects. γ_i is industry fixed effects, α_c and ω_t are country and year fixed effects, and ε_{cit} is the error term. One might argue that the valley period is almost flat and does not contain any significant shocks. We actually take advantage of this period to use it as a placebo shock, meaning that oil countries are expected to perform similar to non-oil countries during that time, as there are no significant movements in international oil prices (Smith, 2014). Corden and Neary (1982) suggest that testing the oil price shock should be applied to oil exporters exclusively, not oil importers (even if these countries produce oil, where they can benefit from a bust). So here we take out the oil net importers (shown in red in Table 4-2) to be able to compare between the two shocks. Corden and Neary (1982) argue that the effects of oil price shock are similar to those of an oil discovery.

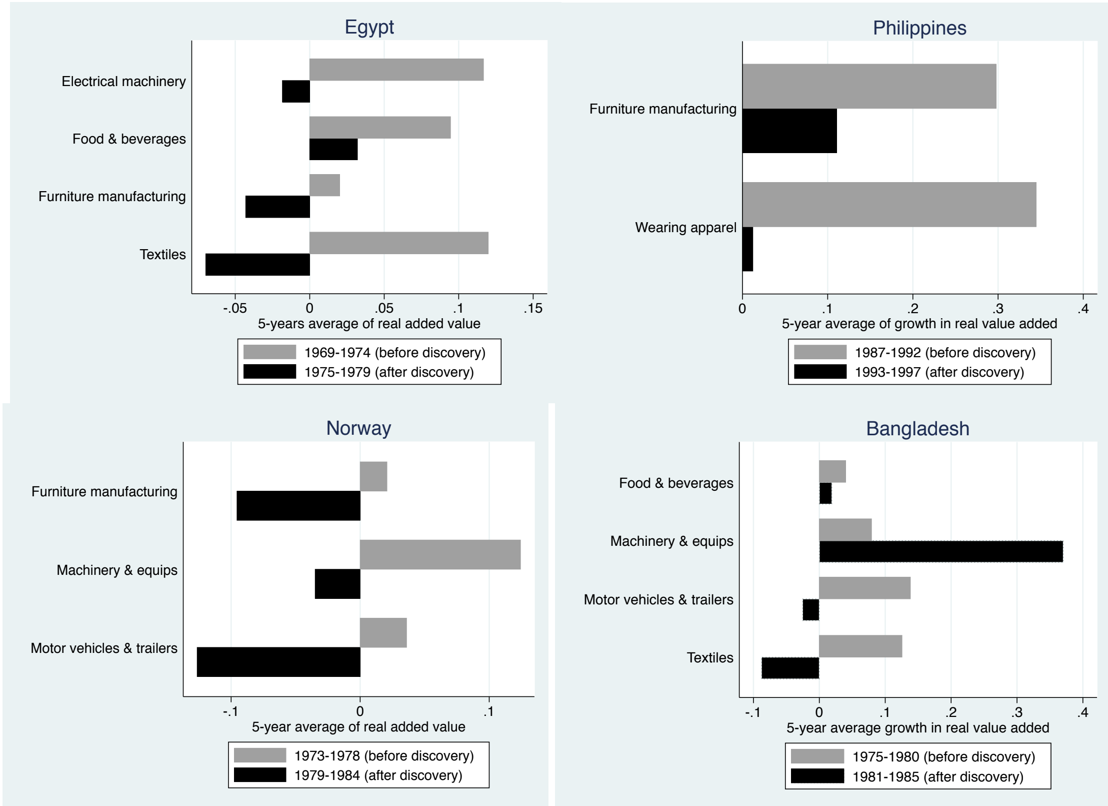
Table 4-2: Treatment group countries, oil price boom and bust

Country	UNIDO	Country	UNIDO
Albania	Yes	Libya	Yes
Algeria	Yes	Malaysia	Yes
Bahrain	Yes	Mexico	Yes
Bolivia	Yes	Nigeria	Yes
Canada	Yes	Oman	Yes
Colombia	Yes	Qatar	Yes
Ecuador	Yes	Saudi Arabia	Yes
Egypt	Yes	Syria	Yes
Gabon	Yes	Trinidad and Tobago	Yes
Indonesia	Yes	Tunisia	Yes
Iran	Yes	United Arab Emirates	Yes
Iraq	Yes	United States	Yes
Kuwait	Yes	Venezuela	Yes

Notes: Countries in red are net importer oil producing countries and are excluded from the main regression; we add them in a separate regression – results are shown in Table C-4.

Before we engage in estimating the average effect, it is probably worthwhile analysing some country-specific trends. In Figure 4-2 we examine the effect of giant oil discoveries on the 5-year average value added. The countries we choose for this graph are varied in terms of political backgrounds and economic development. We observe that value added in exportable industries grows relatively more slowly than for other industries after giant oil discoveries. The discoveries displayed in these figures are not necessarily exclusive; there might be more discoveries in other years. However, we chose to show discoveries 5-10 years apart from each other to allow us to calculate the 5-year average in these figures.

Figure 4-2: Value added growth before and after selected giant discoveries in different countries with various backgrounds



Notes: The x-axes report the 5-year average growth in real value added in percentage terms; the y-axes show selected exportable industries in each country. Data sources: value added data is from UNIDO (2015). Oil discovery data is from Lei and Michaels (2014).

4.5 Empirical Results

4.5.1 Specification checks

Before testing the impact of giant oilfield discovery on manufacturing, we test the underlying identification assumption – that giant oilfield discoveries are exogenously timed with respect to underlying economic conditions – by attempting to predict the discoveries using economic variables. To do that, we estimate a fixed-effects logit model, where the independent variables are lags of manufacturing measures in different sectors and other economic variables and the dependent variable is a dummy variable equal to one in the year of a giant oilfield discovery. As shown in Table 4-3, we find that the key variables of interest – manufacturing value added and employment – as well as changes in other economic and political variables do not predict giant oil discoveries. We assign changes to differences in two years before discovery to be able to tackle any moves in investments and income that could occur at the beginning or end of the year prior to discovery.

Table 4-3: Do political and economic variables predict giant oil discoveries?

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Previous year's polity2 score	0.005 (0.020)					-.0331 (.0403)				
Previous year's real value added in manufacturing		1.57e-11 (1.09e-10)								
Previous year's employment in manufacturing			4.56e-08 (4.20e-08)							
Previous year's growth				-3.58e-14 (9.60e-14)						
4-year lagged oil prices					-.0105 (.0079)	.00402 (.0156)				
Change in income pc							-0.00006 (0.0001)			
Change in government expenditure								-0.0174 (0.228)	-0.0118 (0.0098)	
Change in investments						.0309 (.0216)		0.0359 (0.022)		0.0277 (0.0205)
Observations	2672	24448	27063	2092	2130	384	2256	481	1057	481

Notes: reported coefficients are from a fixed-effects logit model of the probability of a giant oil discovery occurring in a given year. Robust standard errors are in parentheses. Columns 5 and 6 show the impact of lagged oil prices on giant oil discoveries. We chose 4-year lag to allow for the time usually taken between exploration and announcement; however, we did not find any shorter lags significant (3, 2, 1 years). The only significant oil price lag is 5-year lag but only at the 10% level; this estimate becomes insignificant if we control for variables in Column 6. Any lag more than 5 years becomes insignificant as well. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.5.2 Baseline specification and results

After explaining our identification strategy, we now examine the model's first assumption that giant oilfield discoveries harm tradable manufacturing. We begin by examining the impact of discoveries on the manufacturing value added. Table 4-4 shows the results of estimating equation 4-1 with year-on-year difference in the log of total manufacturing value added in industry i in country c over the time period examined in this paper, ranging from 1962-2012, depending on data availability as the dependent variable.

Table 4-4: Giant oil discoveries and sectoral growth: manufacturing added value

Dependent variable: *annual growth rate of value added in industry i in country c (logged)*							
Outcome in year:	*j=0*	*j=5*			*j=10*		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Oil discovery	0.003						
	(0.007)						
Oil discovery (t+j)		-0.007			-0.018***		
		(0.007)			(0.007)		
Oil discovery (t+j) *Exportability index (1)			-0.009			-0.015	
			(0.009)			(0.009)	
Oil discovery (t+j) *Exportability index (2)				-0.006			-0.014
				(0.014)			(0.014)
Past giant discoveries (t-10)	0.002	0.006***	0.005***	0.005***	0.006***	0.005***	0.005**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Industry share (t-1)	-0.532***	-1.057***	-1.062***	-1.061***	-1.067***	-1.072***	-1.071***
	(0.044)	(0.073)	(0.073)	(0.073)	(0.071)	(0.072)	(0.072)
Observations	49481	56416	56416	56416	55908	55908	55908
R^2	0.038	0.038	0.038	0.038	0.038	0.038	0.038

Notes: all regressions include country, year and industry fixed effects. Robust standard errors clustered at the country level are reported in parenthesis. ***, ** and * denote significant at the 1, 5 and 10% level. Exportability index (1) is a dummy that takes on a value of 1 if an industry's ratio of exports to value added is greater than the median value and is 0 otherwise, from Rajan and Subramanian (2011). Exportability index (2) is a dummy that takes on a value of 1 for ISIC industries 15-21, and 0 otherwise (author calculation).

Column 1 shows the impact on the same year of discovery *t*, while Column 2 shows the impact 5 years after discovery on total manufacturing value added. We choose to start from (t+5) as we consider the oilfield production lag, which is the number of years between the giant oil discovery announcement and the physical production commencement, usually takes between 4 to 6 years on average (Arezki et al., 2015b). Then we continue to (t+10) to examine the structural change in the long run.

Interestingly, the number of giant oil discoveries in the past 10 years continues to have a significant positive impact on value added, indicating that if a country has more giant discoveries in the past – and therefore possibly more resource dependent – the value added growth is positively correlated with more discoveries. In addition, we also control for the industry j's value added share in total manufacturing a year prior to discovery in all columns. We find a consistent pattern that higher initial share of the tradable industries is correlated with less growth in value added. The results so far agree with a number of papers in the literature, by showing that resource abundance does not have a major negative effect on manufacturing. For example, Bjørnland and Thorsrud (2016) show that value added in manufacturing industries increases following resource booms, as these industries were boosted by government spending that increased through oil revenues.

Our strategy continues to track the impact in the medium-long run to consider the production lag and structural changes within the economy. Columns 2, 3 and 4's results show that the impact went in the opposite direction after 5 years, as growth of value added is now declining in our treatment group.

In columns 3 and 4 we disaggregate the manufacturing industries depending on their exportability following Rajan and Subramanian (2011). Columns 3 and 4 show that value added in the tradable sector grows relatively slower than it does in countries with no giant oil discoveries. The impact is insignificant but still negative in both columns. The difference between the two columns is that the groups of industries included in the index exportability 1 are usually more labour-intensive and more frequent in developing countries, where industries in exportable 2 index are usually more capital-intensive and more frequent in developed countries in our sample.

In the longer term, columns 5, 6 and 7 show the impact 10 years after discovery. We can see that the effect has now more statistical significance at the 1% level, indicating that manufacturing value added is negatively affected by resource discoveries in the long run. Manufacturing value added grew by an average of almost 2 percentage points per year in countries with giant oilfield discoveries, slower than in countries with no discoveries. The negative effects on both exportability indices 1 and 2 industries are now higher but still insignificant.

Next, we test if there are other manufacturing outcomes affected by the resource booms. Table 4-5 reports the results of equation 4-1 with a different manufacturing outcome: employment.

Table 4-5: Giant oil discoveries and sectoral growth: manufacturing employment

Dependent variable: *annual growth rate of employment in industry i in country c (logged)*							
Outcome in year:	*j=0*	*j=5*			*j=10*		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Oil discovery	-0.010**						
	(0.004)						
Oil discovery (t+j)		-0.009**			-0.004		
		(0.004)			(0.004)		
Oil discovery (t+j) *Exportability index (1)			-0.007			-0.005	
			(0.005)			(0.006)	
Oil discovery (t+j) *Exportability index (2)				-0.009			-0.002
				(0.009)			(0.010)
Past giant discoveries (t-10)	-0.002	0.000	-0.000	-0.000	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Industry share (t-1)	-0.533***	-0.442***	-0.442***	-0.442***	-0.436***	-0.436***	-0.435***
	(0.033)	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)
Observations	56192	63010	63010	63010	61723	61723	61723
R^2	0.041	0.033	0.033	0.033	0.033	0.033	0.033

Notes: all regressions include country, year and industry fixed effects. Robust standard errors clustered at the country level are reported in parenthesis. ***, ** and * denote significant at the 1, 5 and 10% level. Exportability index (1) is a dummy that takes on a value of 1 if an industry's ratio of exports to value added is greater than the median value and is 0 otherwise, from Rajan and Subramanian (2011). Exportability index (2) is a dummy that takes on a value of 1 for ISIC industries 15-21, and 0 otherwise (author calculation).

Columns 1 and 2 in Table 4-5 show that total manufacturing employment becomes negatively affected by discoveries as soon as the discovery is announced and continues about 5 years after discovery. However, both exportable indices 1 and 2 interactions are also negatively affected but not statistically significant. So, if both exportable sectors were not significantly affected, would this indicate that other non-tradable manufacturing sectors are the ones negatively affected – contradicting the core model of Dutch disease? We will still investigate the effect on wages to develop the full picture. These results could support the previous findings in the literature that the governments try to support the tradable sectors through more spending and investing, by trying to keep the employees in their jobs as much as possible. The impact is still negative 10 years after discovery, as shown in columns 5, 6 and 7 but with no statistical significance, indicating that the effect on manufacturing employment occurs earlier than it does in the value added. Wages will give an additional insight into that effect.

Table 4-6: Giant oil discoveries and sectoral growth: manufacturing wages

Dependent variable: *annual growth rate of real wages in industry i in country c (logged)*							
Outcome in year:	*j=0*	*j=5*			*j=10*		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Oil discovery	0.004						
	(0.006)						
Oil discovery (t+j)		-0.003			-0.022***		
		(0.006)			(0.006)		
Oil discovery (t+j) *Exportability index (1)			0.001			-0.021***	
			(0.007)			(0.008)	
Oil discovery (t+j) *Exportability index (2)				0.002			-0.026**
				(0.011)			(0.012)
Past giant discoveries (t-10)	0.002	0.005***	0.004***	0.004***	0.004***	0.003**	0.003*
	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Industry share (t-1)	-0.433***	-0.508***	-0.508***	-0.508***	-0.306***	-0.309***	-0.307***
	(0.034)	(0.034)	(0.034)	(0.034)	(0.032)	(0.032)	(0.032)
Observations	50577	57503	57503	57503	52396	52396	52396
R^2	0.062	0.053	0.053	0.053	0.056	0.056	0.056

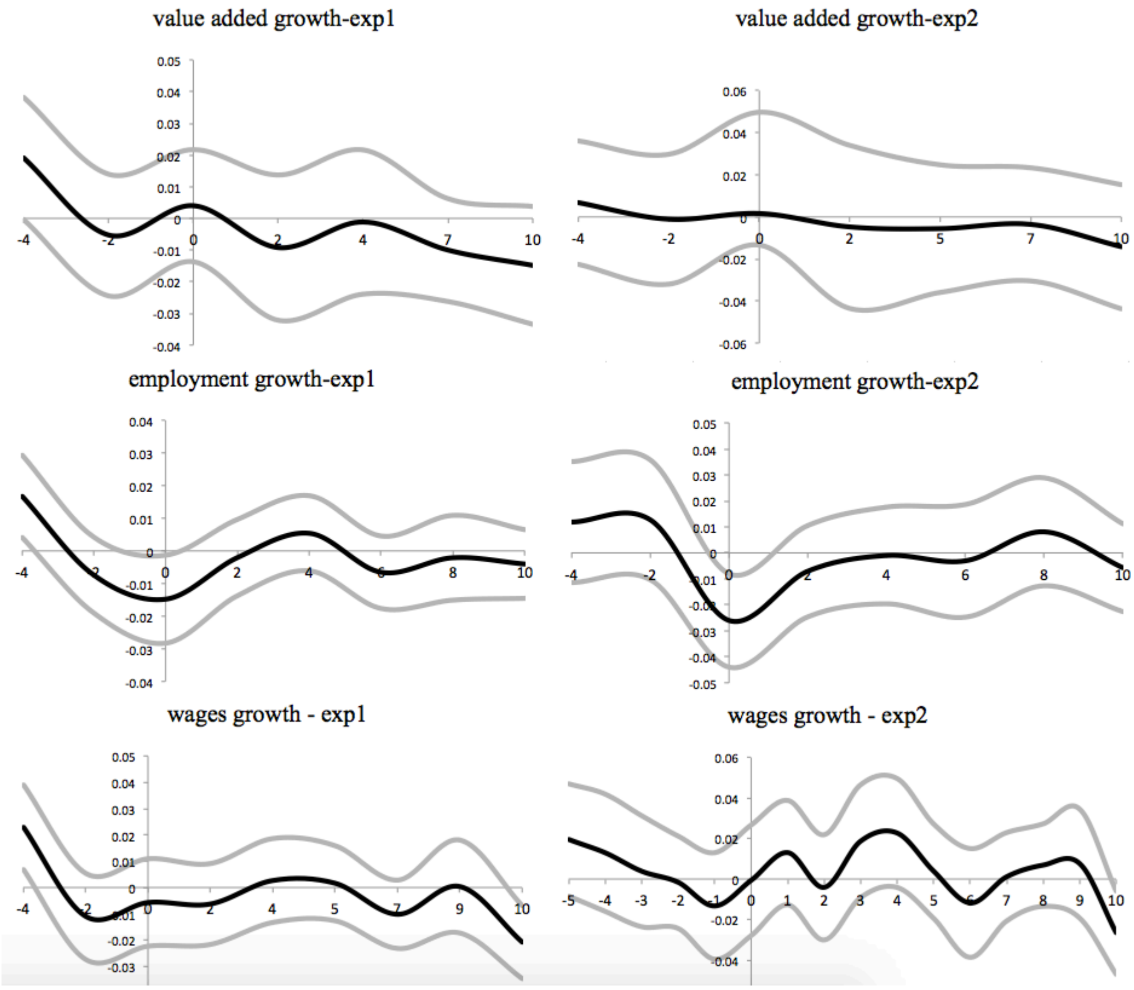
Notes: all regressions include country, year and industry fixed effects. Robust standard errors clustered at the country level are reported in parenthesis. ***, ** and * denote significant at the 1, 5 and 10% level. Exportability index (1) is a dummy that takes on a value of 1 if an industry's ratio of exports to value added is greater than the median value and is 0 otherwise, from Rajan and Subramanian (2011). Exportability index (2) is a dummy that takes on a value of 1 for ISIC industries 15-21, and 0 otherwise (author calculation).

The Dutch disease theory predicts that an oil boom should push up wages in the economy as a whole, which in turn reduces employment in the non-booming sector.

Columns 5, 6 and 7 of Table 4-6 show that the impact on wages takes more time to get through, as much as 10 years after discovery (we still find a negative impact 5 to 9 years after discovery but with insignificant coefficients). When examining the effect on wages 10 years after discovery, we get significant negative results. We can conclude that the impact on tradable manufacturing sector wages is generally negative, and becomes more significantly negative in the medium-long run (10 years after discovery), lagging behind the negative impact on employment. Some papers in the literature claimed that wages and value added are *channels* to declining employment following resource booms. Our results bring a different perspective:

First, we argue that declining output and wages are responding to the declining employment in manufacturing, by taking around five more years to reach the significant effect. Second, despite the insignificant negative effect on the tradable industries in employment and value added coefficients we find so far, the fact that the coefficients are negatively affected could indicate that the manufacturing sector showed fewer opportunities and became less attractive for workers, who might have shifted to other parts of the economy to meet the increasing local demand with probably higher wages. This argument is shown in the tradable industries wages coefficients, where both coefficients were negatively affected around 10 years after discovery as a result of less demand for these jobs. This also might indicate that governments are trying to support the tradable sector for some time, as suggested by the literature, but structural change takes place in the long run. Figure 4-3 plots these effects 4 years before (t-4) and 10 years after (t+10) the discovery shock.

Figure 4-3: Impact of giant oil discoveries on manufacturing growth: in value added, employment and wages



Notes: The x-axes report the number of years before or after t, ranging from t-5 to t+10, depending on data availability. The black lines show the estimated coefficients and the grey lines show the 95% confidence intervals based on robust standard errors, which are clustered by country. All regressions control for previous discoveries (t-1 to t-10) and initial manufacturing share, and include industry, country and year fixed effects. Exp1 indicates growth in exportable manufacturing industries in group "exportable 1" and Exp2 indicates growth in exportable manufacturing industries in group "exportable 2." Details on variable construction can be found in the data section of the paper.

4.5.3 Transmission channels

Following our hypothesis above, as we are assessing the manufacturing industries, we can test more channels affecting these industries by measuring the real exchange rate appreciation after resource booms. After that, and following Rajan and Subramanian (2011) and Bjørnland and Thorsrud (2016), we test the role of the country's openness in the tradable sectors, to be able to see if globalisation and openness have a role in this structural change.

Table 4-7: Real exchange rate appreciation and oil discoveries

	Dependent variable: *Excess appreciation*	***Dependent variable:*** *Annual growth rate of manufacturing outcome in industry i in country c (logged)*			
	(1)	(2)	(3)	(4)	(5)
Giant Oil Discoveries (t+5)	-0.011***				
	(0.004)				
Panel A: *dependent variable is annual growth rate of real value added in industry i in country c (logged)*					
RER*Exportability index (1)		0.035***		0.026*	
		(0.013)		(0.014)	
RER*Exportability index (2)			0.007		-0.005
			(0.018)		(0.020)
Oil discovery (t+5)* Exportability index (1)				-0.022*	
				(0.014)	
Oil discovery (t+5)* Exportability index (2)					-0.009
					(0.022)
Observations	57684	14373	14373	13145	13145
R^2	0.68	0.049	0.049	0.052	0.051
Panel B: *dependent variable is annual growth rate of employment in industry i in country c (logged)*					
RER*Exportability index (1)		0.003		0.000	
		(0.005)		(0.005)	
RER*Exportability index (2)			0.002		-0.002
			(0.009)		(0.010)
Oil discovery (t+5)* Exportability index (1)				-0.009*	
				(0.005)	
Oil discovery (t+5)* Exportability index (2)					-0.011
					(0.008)
Observations		65162	65162	58031	58031
R^2		0.037	0.037	0.034	0.034
Panel C: *dependent variable is annual growth rate of real wages in industry i in country c (logged)*					
RER*Exportability index (1)		0.035***		0.050***	
		(0.010)		(0.008)	
RER*Exportability index (2)			0.036**		0.044***
			(0.014)		(0.012)
Oil discovery (t+10)* Exportability index (1)				-0.028***	
				(0.008)	
Oil discovery (t+10)* Exportability index (2)					-0.031**
					(0.012)
Observations		56345	56345	49058	49058
R^2		0.056	0.056	0.061	0.059

Notes: full details of regression (1) can be found in Table C-3 in the appendices. All regressions include country, year and industry fixed effects. Robust standard errors clustered at the country level are reported in parenthesis. ***, ** and * denote significant at the 1, 5 and 10% level. All regressions control for the value added share one year prior to discovery (t-1). Regressions (4) and (5) control for past discoveries: the number of years with discoveries from t-10 to t-1. Regressions for Panel A value added (t+10) give the same results as (t+5) and are available upon request.

We follow Rajan and Subramanian (2011) in this strategy, they find that exchange rate appreciation is the channel for Dutch disease where aid harmed tradable manufacturing when they introduced both coefficients in the same regression. They use the methodology in Rajan and Zingales (1998) that suggests that "one way to check whether a channel is at work is to see whether industries that might be most affected by a channel grow differentially (faster or slower depending on the nature of the effect) in countries where that channel is likely to be more operative. The industry characteristics we are interested in is the degree to which an industry's competitive position is affected by exchange rate appreciation, the channel is real exchange rate appreciation" – in addition to trade openness – and countries that get oil discoveries are likely to be the ones where the channel is most operative. This approach gives an advantage to test all these effects simultaneously, by testing for these individual relationships in the data.

In Table 4-7, we provide evidence that excess appreciation is *not* the channel through which resource discoveries affect exports, which also agrees with the core Dutch disease model. In Column 1, we show the simple reverse correlation between excess appreciation and giant oil discoveries, which is statistically significant at the 1% level, indicating that the coefficients have opposite effects on the manufacturing outcome[19]. If real appreciation was the channel, then like giant oil discoveries, it should have a negative impact on the tradable industries. We therefore test this result further and estimate equation 4-2, starting with Panel A in Table 4-7, where the outcome is annual growth in value added; columns 2 and 3 show that the interaction term between excess appreciation and both of our exportability measures is positive, although insignificant

[19] We got mixed results for the effect of giant oil discoveries on real exchange rate appreciation for each year after discovery up to 10 years. Although most of these results are significant at the 1 and 5% level, the mixed signals prove that the impact is temporary, as indicated by Corden and Neary (1982), or different from one country to another depending on its oil dependency and other factors, as suggested by Bjørnland and Thorsrud (2016).

for exportability measure 2. These results suggest that excess appreciation has a reverse effect of resource discoveries on growth in value added of tradable industries. And this is the same suggestion we get from the remaining panels B and C for employment and wages in tradable industries. This shows that excess exchange rate appreciation does not provide the same effect of resource discoveries on the growth in tradable manufacturing industries.

To check these results, we introduce both the discoveries and excess appreciation interactions in the same regression as shown in columns 4 and 5. If the excess appreciation was the main channel for the causal impact of resource discoveries on tradable manufacturing, the effect of the discovery interaction should be weakened in the presence of the excess appreciation interaction compared to the baseline results[20]. We do not find these assumptions in all results. In Panel A, the coefficient estimate of the excess appreciation interaction for exportability measure 1 is now significant, compared to Table 4-4. In Panel B, the coefficient estimate of the excess appreciation interactions remained insignificant with less magnitude. The discovery interactions are similar to the results of growth in manufacturing employment in Table 4-5. In Panel C, the coefficient estimates of the excess appreciation interactions remain significant, while those for the discovery interactions increase in magnitude.

These mixed results we get after introducing the excess appreciation measures provide evidence that excess appreciation cannot represent the channel through which resource discoveries influence the tradable industries. This suggestion agrees with the core model of the Dutch disease, when Corden and Neary (1982) emphasised that even if the resource boom leads to real exchange rate appreciation, real exchange rate appreciation

[20] We follow Rajan and Subramanian (2011) in this strategy, where they find that exchange rate appreciation is the channel for Dutch disease where aid harmed tradable manufacturing when they introduced both coefficients in the same regression.

should not be taken as a cause of de-industrialisation. The paper continues *"it – real appreciation – should more properly be seen as a symptom of the economy's adjustment towards the new post-boom equilibrium" (p. 841)*. These results also agree with Cashin et al. (2004) in an IMF study presenting evidence that for the majority of commodity exporting countries, it is the real exchange rate which adjusts to restore the long-run equilibrium with commodity booms, and it only takes half-life of adjustment of real exchange rates to equilibrium of about 10 months[21]. The study also suggests that the long-run real exchange rate of "commodity currencies" is not constant but is time varying, depending on the commodity booms. Speculatively, the impact of real appreciation on the tradable industries growth we find could possibly be temporary, while it is part of the new equilibrium and is not directly caused by the resource booms. The resource discoveries interactions continued to have the significant negative impact even after including the real appreciation interaction, giving more validity to our baseline results.

Even if the real exchange rate appreciates in resource countries following resource discoveries, their export competitiveness could decline. At the same time, imports from other non-resource countries become cheaper. Therefore, government policies can play a major role in determining and supporting the tradable sector when the real exchange rate fluctuates. One reasonable way to test these policies is through the oil countries' openness measures. We follow the same strategy used for testing the role of exchange rate appreciation to test if openness could possibly be the channel of treatment. To

[21] The half-life is the length of time it takes for a unit impulse to dissipate by half (Cashin et al., 2004).

examine the openness and trade liberty we use openness from Penn World Table[22], which offers a wide range of data in our panel.

In Table 4-8 we include the openness measure interacting with our exportability indices in equation 4-2 by replacing the real appreciation interaction variables by the openness interaction variables. We find that the oil discovery interactions are still keeping the negative signs even after including the openness interactions, giving more validity to our baseline results. Yet these negative signs became more prominent in statistical significance, which might suggest that openness is a better explaining channel than real appreciation. Columns 1 and 2 for all panels test the correlation between openness and manufacturing outcomes without including the discoveries; the results show a negative impact in all panels, which is the same sign we got from discoveries, unlike the positive impact we got from real appreciation interactions in Table 4-7.

[22] We use PWT 6.3 because new versions of PWT do not include openness anymore.

Table 4-8: Openness and the tradable sector

	Dependent variable: *Annual growth rate of manufacturing outcome in industry i in country c (logged)*			
	(1)	(2)	(3)	(4)
Panel A: *dependent variable is annual growth rate of real value added in industry i in country c (logged)*				
Open*Exportability index (1)	-0.006		-0.004	
	(0.018)		(0.029)	
Open *Exportability index (2)		0.036		0.004
		(0.025)		(0.038)
Oil discovery (t+5)* Exportability index (1)			-0.003	
			(0.016)	
Oil discovery (t+5)* Exportability index (2)				-0.015
				(0.022)
Observations	46002	49045	46002	46002
R-squared	0.046	0.051	0.046	0.047
Panel B*: dependent variable is annual growth rate of employment in industry i in country c (logged)*				
Open *Exportability index (1)	-0.006		-0.028*	
	(0.010)		(0.015)	
Open *Exportability index (2)		-0.007		0.032
		(0.01)		(0.018)
Oil discovery (t+5)* Exportability index (1)			-0.024***	
			(0.009)	
Oil discovery (t+5)* Exportability index (2)				-0.028**
				(0.012)
Observations	54690	54690	54690	54690
R-squared	0.038	0.038	0.038	0.038
Panel C: *dependent variable is annual growth rate of real wages in industry i in country c (logged)*				
Open *Exportability index (1)	-0.002		0.074***	
	(0.011)		(0.015)	
Open *Exportability index (2)		-0.016		0.062**
		(0.019)		(0.026)
Oil discovery (t+10)* Exportability index (1)			-0.064***	
			(0.012)	
Oil discovery (t+10)* Exportability index (2)				-0.061***
				(0.019)
Observations	45045	45045	48343	48343
R-squared	0.059	0.059	0.059	0.059

Notes: all regressions include country, year and industry fixed effects. Robust standard errors clustered at the country level are reported in parenthesis. ***, ** and * denote significant at the 1, 5 and 10% level. Regressions (3) and (4) control for past discoveries: the number of years with discoveries from t-10 to t-1. Observations which interacted with openness are multiplied by 100 in all panels for better reading.

In more detail, columns 3 and 4 of Panel A show that the value added outcomes affected by resource discoveries are still both insignificant, compared to Table 4-4. We now turn to employment in Panel B that was negatively insignificant in Table 4-6, but columns 3 and 4 in Table 4-8 show that including the openness interaction has turned oil discovery interactions for both exportability indices 1 and 2 to be statistically significant with higher magnitude, indicating that employment is highly affected by the resource country's openness and trade policies, whether it exports labour-intensive or capital-intensive products. The insignificant coefficients of value added interactions we still find in Table 4-8 might indicate that governments try to support the tradable sectors through investments and spending, but the workers (as the labour market is elastic and flexible within one country) might be moving towards more demanding opportunities in the non-tradable sectors such as non-traded manufacturing or services; this suggestion agrees with Michaels (2011) and Bjørnland and Thorsrud (2016).

To test this hypothesis, we examine the impact on wages in Panel C, as wages in the tradable sectors have been negatively affected by oil discoveries in Table 4-6. Columns 3 and 4 of Table 4-8 report the results for wages. The results show that the coefficients of oil discovery interactions are still negative and significant but also with higher magnitude after including the openness interactions.

Rajan and Subramanian (2011) use this strategy to test if real appreciation is the channel where aid affects manufacturing growth, and they find it does. We do agree with Bjørnland and Thorsrud (2016) that the more open the economy, the more it gets affected by resource booms. They also argue that real exchange rate appreciation does not necessarily happen in all oil countries; it did not happen in Norway, for example, as a result of resource booms where it showed evidence of real depreciation instead. In Australia, the appreciation was temporary and later it was rather real depreciation.

These results have a number of explanations. First, value added and wages take more time to experience the full effect of resource discoveries, even after adding the openness interaction measures. Wages might need more time to adjust to the new booming sector fitting into the economy, as production starts after an average of 4-6 years of discovery announcement, and exporting oil in meaningful amounts might need more than 2-3 years. Second, the demand on labour in the tradable industries is affected by both international and local demand on the tradable products – the more the country is open to international trade the more the tradable industries are affected. These results support the classic model of Dutch disease. Introducing the interaction with openness actually increased the magnitude of the negative impact on tradable manufacturing employment and wages. Intuitively, we agree with the core model of Dutch disease showing that the tradable sector is the mostly hurt by resource discoveries.

4.5.4 Commodity price shocks: oil booms and busts

In this section, we move to our second measure of resource booms: oil price booms and busts. The results are shown in Table 4-9, based on equation 4-3. Columns 1, 4 and 7 show the impact on total manufacturing measures: total value added, total employment and total wages during the years of the two booms, bust and valley. In accordance with the core model of the Dutch disease, the boom had a significant negative impact on the three total manufacturing outcomes. Columns 1, 2 and 3 show that the bust seems to have more significant negative impact on the value added than the boom. In addition, the exportable industries of indices 1 and 2 were mixed with insignificant coefficients. These results support our baseline findings that manufacturing is negatively affected by oil booms, whether it was an oil discovery or an oil price shock.

Table 4-9: Impact of oil price boom, bust and valley on manufacturing

	Value added			Employment			Wages		
	All	Interacted* Exp Index 1	Interacted* Exp Index 2	All	Interacted* Exp Index 1	Interacted* Exp Index 2	All	Interacted* Exp Index 1	Interacted* Exp Index 2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Boom	-0.088	0.012	0.016	-0.170***	-0.006	0.014	-0.143**	0.012	0.026
	(0.070)	(0.024)	(0.036)	(0.060)	(0.018)	(0.024)	(0.061)	(0.020)	(0.028)
Bust	-0.128***	-0.025	-0.065	-0.111***	-0.008	-0.012	-0.141***	-0.004	-0.046
	(0.048)	(0.032)	(0.046)	(0.031)	(0.019)	(0.026)	(0.037)	(0.029)	(0.040)
Valley	-0.088	0.026	0.020	-0.102***	-0.006	0.001	-0.059	-0.007	-0.006
	(0.058)	(0.034)	(0.053)	(0.037)	(0.020)	(0.030)	(0.046)	(0.024)	(0.036)
Industry	-0.388***	-0.394***	-0.387***	-0.411***	-0.411***	-0.410***	-0.326***	-0.323***	-0.325***
share	(0.094)	(0.094)	(0.094)	(0.061)	(0.061)	(0.061)	(0.075)	(0.076)	(0.076)
Obs	7680	7680	7680	8046	8046	8046	7709	7709	7709
R^2	0.04	0.04	0.04	0.05	0.05	0.05	0.06	0.06	0.06

Notes: all regressions include country, year and industry fixed effects. Robust standard errors clustered at the country level are reported in parenthesis. ***, ** and * denote significant at the 1, 5 and 10% level. "All" is all manufacturing industries. Exportability index (1) is a dummy that takes on a value of 1 if an industry's ratio of exports to value added is greater than the median value and is 0 otherwise, from Rajan and Subramanian (2011). Exportability index (2) is a dummy that takes on a value of 1 for ISIC industries 15-21, and is 0 otherwise (author calculation).

Columns 4, 5 and 6 report the results of manufacturing employment. Column 4 shows that total employment is affected negatively by all three shocks. However, both exportable indices 1 and 2 are not affected significantly by the shocks.

Columns 7, 8 and 9 report the results of manufacturing wages. Total manufacturing wages declined significantly during the boom and bust. However, both tradable industries' wages grew positively during the boom, and negatively during the bust and valley with insignificant coefficients.

In general, the bust has a stronger and more negative impact on manufacturing than the boom. This could indicate that oil countries tend to support the manufacturing sector during the boom, as they are receiving more oil revenues and able to spend more on these industries. As explained earlier, we only include net exporters in the main regression in Table 4-9. To examine the oil price shock impact on all oil countries including net importers please refer to Table C-4 in the appendices. The results are mainly the same, as the total manufacturing coefficients in value added, employment and wages are all negatively affected. One interesting difference is the significant negative effect on tradable industries value added of index 1 during the bust, which could be explained by the fact that it is more labour-intensive than index 2, as the declining employment in manufacturing will harm these types of industries more significantly.

One confounding factor with "all manufacturing" coefficients in columns 1, 4 and 7 is that it includes industries linked to the oil industry and they may be more prominent. But even with that in consideration, we still find negative coefficients in all three outcomes despite the fact that the oil boom would clearly support oil-related manufacturing industries.

Our results so far agree with Ismail (2010) in finding that manufacturers in oil-exporting countries with more open capital markets are more negatively affected by oil price shocks. The results also agree with Rodrik (2016) who finds that the labour-intensive sector is the one most harmed by globalisation. We add that the labour-intensive sector is also the one most hurt by resource booms, especially if the resource country is more open to trade. The reason is that the share of these labour-intensive sectors in the international market is relatively small, provided by a small number of developing countries.

Our results show that most contractions in the manufacturing sector could be explained by the contraction in the tradable industries. These results challenge results in recent papers by Smith (2014), Allcott and Keniston (2014) and Bjørnland and Thorsrud (2016), where they find a positive impact of resource discoveries on manufacturing. A major difference in our approach is that we can identify the impact on the tradable industries; non-tradable manufacturing industries might benefit from the resource booms through increased local demand and increased government spending and investments (Michaels, 2011), but this is not within the scope of our paper. Another difference is that some papers focus on manufacturing in developed countries, such as Allcott and Keniston (2014) focusing on the United States and Bjørnland and Thorsrud (2016) focusing on Norway and Australia, while others focus on developing countries such as Smith (2014). We add additional scope by examining the impact in both developed and developing countries together while considering the differences in their tradable industries. Moreover, our estimates show that the decline in wages and value added in the manufacturing sector came as a *result* of the decline in employment. This argument contrasts with results in the literature[23], where they argue that wages are rather a *channel* for the total manufacturing sector final impact.

4.5.5 Manufacturing growth deceleration episodes

After showing the negative impact of resource booms on manufacturing growth, we now turn to an additional measure and see if this noted slowdown is sustainable. In this section, we study 40 episodes of manufacturing slowdowns. A slowdown is defined as a significant and sustained decrease in manufacturing value added growth from one three-year period to the next. Following Freund and Pierola (2012) on growth accelerations, we use their filter to identify episodes of manufacturing slowdowns. A slowdown must satisfy the following criteria:

a) Real average manufacturing value added growth over 3 years is below -2%.
b) Real average 3-year manufacturing value added growth decreases by one third from the previous 3-year average and is at least two percentage points below the previous three-year average.

[23] Allcott and Keniston (2014) among others

c) Average growth during the drop, excluding the weakest year of growth, is below than average growth before the drop.

As Freund and Pierola (2012) suggest, condition (a) ensures that value added growth is below the world average for a slowdown. Condition (b) ensures that growth decreases significantly from the previous three-year period and is not just a trend, and condition (c) excludes slowdowns that are due to 1 year of very weak growth. To identify the slowdowns, we continue using the same INDSTAT2 dataset from UNIDO we used in previous sections. After applying the criteria mentioned above, we obtain 40 episodes of manufacturing value added slowdowns between 1971-2011.

Next, we examine if these slowdown episodes are associated with our main external variation: giant oil discoveries. We aim to see if our results in previous sections are sustainable and are not just a trend. We use the following equation to assess the impact of giant oil discoveries on manufacturing value added slowdown episodes:

$$Y_{ct} = \beta_1 Disc_{ct} + \beta_2 X_{ct} + \gamma_i + \alpha_c + \omega_t + \varepsilon_{cit} \qquad (4\text{-}4)$$

where Y_{ct} is the outcome of interest, which is a dummy variable that takes the value of 1 if the year falls under the slowdown criteria mentioned above in country c in year *t*, and the value of 0 otherwise. $\mathrm{Disc_{it}}$ is an indicator for the discovery of a giant oilfield in country c in year *t*. $\mathrm{X_{ct}}$ is the number of years with giant oil discoveries in country c from t-10 to t-1. γ_i is industry fixed effects, α_c and ω_t are country and year fixed effects, and ε_{cit} is the error term. β_1 is our main interest.

Column 1 in Table 4-10 shows the impact on the same year of discovery *t* on the slowdown episodes, while Column 2 shows the impact after 5 years of discovery. We choose t+5 following our baseline strategy, as we consider the oilfield production lag, which is the number of years between the giant oil discovery announcement and the physical production commencement that usually takes between 4 to 6 years on average (Arezki et al., 2015b).

Table 4-10: Manufacturing slowdowns and oil discoveries

Dependent variable: *manufacturing value added slowdown episodes*		
	(1)	(2)
Oil discovery	0.000	
	(0.002)	
Oil discovery (t+5)		0.008***
		(0.002)
Past giant discoveries	0.003***	0.003***
	(0.001)	(0.001)
Observations	47587	54096
R^2	0.112	0.093

Notes: all regressions include country, year and industry fixed effects. Robust standard errors clustered at the country level are reported in parenthesis. ***, ** and * denote significant at the 1, 5 and 10% level. Past discoveries is the number of years with giant oilfield discoveries from t-10 to t-1. The dependent variable, slowdown episodes are calculated following Freund and Pierola (2012). We do not run the regression for oil discovery (t+10), as data gets much smaller with the bigger lag, and might result in misleading effects.

In the same year of giant oil discoveries, Column 1 shows that there is no significant impact on slowdown episodes. Only 5 years after discovery, Column 2 shows that giant oil discoveries increase the probability of going through a slowdown episode in manufacturing value added with a highly significant coefficient. These results support our baseline results, where we suggest that giant oil discoveries lead to a decline in manufacturing value added growth starting from 5 years after discovery.

4.5.6 Robustness checks

To ascertain that our results are not driven by other factors, and to further tackle the issue of endogeneity, we subject the main results to several robustness checks and alternative specifications. First, one concern is that giant oil discoveries as a dummy variable would be misleading, and thus we substitute the independent variable by the value of giant oil discoveries instead. This strategy is applied by Cotet and Tsui (2013) and more recently by Arezki et al. (2015b), where they construct a net present value (NPV) of the oil discovery as a percentage of GDP at the time of the discovery. For our robustness checks, we use data from Cotet and Tsui (2013), which was originally provided by ASPO dataset[24]. The data provided by Cotet and Tsui (2013) covers value of discoveries in all sizes; thus, we eliminate the values of non-giant discoveries and keep only the values of giant discoveries based on our dataset. The results are shown in Table 4-11, and we can see that the results are consistent with our baseline estimates by finding negative effects of discoveries on value added and wages, with small and insignificant effects on employment.

Table 4-11: Value of giant oil discoveries and the tradable industries

Outcome is:	**Value added**			**Employment**			**Wages**		
	All	Interacted* Exp Index 1	Interacted* Exp Index 2	All	Interacted * Exp Index 1	Interacted * Exp Index 2	All	Interacted * Exp Index 1	Interacted * Exp Index 2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Value of giant oil Discoveries pc (log)	-0.270***	-0.195*	-0.238	0.030	0.011	0.055	-0.242***	-0.241***	-0.308**
	(0.093)	(0.107)	(0.193)	(0.042)	(0.059)	(0.104)	(0.064)	(0.081)	(0.131)
Past discoveries	-0.000	-0.000	-0.000	-0.003**	-0.003**	-0.003**	0.000	-0.000	-0.000
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Industry share	-0.557***	-0.559***	-0.559***	-0.514***	-0.518***	-0.518***	-0.387***	-0.389***	-0.389***
	(0.050)	(0.050)	(0.050)	(0.036)	(0.036)	(0.036)	(0.034)	(0.035)	(0.034)
Obs	44462	44508	44540	49684	49742	49782	45370	45428	45468
R^2	0.061	0.061	0.061	0.048	0.048	0.048	0.000	-0.000	-0.000

Notes: All regressions control for the number of years with discoveries from t-10 to t-1, per capita GDP, GDP growth, population and democracy, in addition to country, industry and year fixed effects. Independent variable is the log of value of giant oil discoveries per capita from Cotet and Tsui (2013). "All" is all manufacturing industries. Outcome data source is from UNIDO. Robust standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Second, we use oil reserves as an instrument for oil discoveries, following Cotet and Tsui (2013). The instrument is described by Cotet and Tsui (2013) as the log of oil

[24] ASPO: the Association for the Study of Peak Oil.

reserves data, calculated for each country in any year by subtracting cumulative production from cumulative discovery. Table C-6 in Appendix C shows the instrumental variable estimation based on equation 4-1, after instrumenting the oil discovery interaction terms. The results are robust to this specification and to our previous estimates, indicating that giant oil discoveries have a negative impact on the tradable manufacturing industries. The interaction term is mostly negative in panels *A, B* and *C,* where the outcome variables are value added, employment and wages consecutively.

Third, we follow Bjørnland and Thorsrud's (2016) robustness strategy by showing that the results are robust when using the nominal rather than the real figures for value added and wages. The results are unchanged, as shown in Table C-7 in the appendices.

Fourth, we rerun the baseline regressions using INDSTAT4 data instead of INDSTAT2 from UNIDO's industrial statistics database at the 4-digit level of disaggregation for manufacturing. This data covers fewer countries, and a smaller time range, as it goes back only to 1985. The results remain the same for manufacturing value added, employment and wages as shown in Table C-8 in the appendices.

These results suggest that our main results are not driven by omitted variables and do not suffer from serious endogeneity concerns.

4.6 Conclusion

This paper analyses the effect of two different resource shocks on manufacturing tradable activity in oil countries, adding to the narrow literature on the empirical evidence of Dutch disease theory.

We used giant oilfield discoveries as a resource boom shock. We were able to track structural change in the manufacturing sector following giant oil discoveries and found that manufacturing outcomes in the tradable industries declined significantly. To obtain more empirical evidence on the Dutch disease theory, we also test for the effect of the oil booms and bust as a resource price shock, and find a negative effect as well. We further checked these results through building a growth deceleration episodes variable and were able to show that this negative impact is sustainable and not caused by a trend.

The results taken together suggest that the tradable industries in manufacturing are harmed by the oil shocks in two ways. First, the movement of concentration from the tradable industries to the non-tradable industries within manufacturing harms exports in the long run. Second, the more the economy is open, the more significant is the negative impact on the tradable industries. This suggests that the tradable manufacturing industries will be harmed by the resource shocks through less demand for exports in the international market, which would lead to further adjustments in the economy, as suggested by the Dutch disease theory.

These results empirically support the core Dutch disease model. However, the core model suggests that the boom should increase potential welfare and wages in the entire economy, while we find that wages significantly decline in the manufacturing sector in the long run. Finally, by finding that manufacturing growth declines as an effect of the two resource shocks used in our paper, the results agree with Corden and Neary (1982) that the effects of an oil price shock are similar to those of an oil discovery shock in oil countries.

Chapter 5

Conclusion

This thesis examined new empirical dimensions related to the impact of natural resources on the macro economy: the economic diversification in exports and in employment, the role of institutional quality on that impact, and the heterogeneity within the manufacturing sector. The focus shifted from examining the impact of all natural resources down to examining the impact of oil and gas as a suitable representative of the rest of the natural resources, or at least the mineral resources. Here I summarise the key findings of each chapter and suggest potential aspects for further research.

Chapter 2 examined how natural resource rents could change the U-shaped diversification pattern noted by the literature along the development path. In particular, this chapter asked if resource-rich countries diversify out of resource and nontradable sectors during the development path before finding the perfect area of specialisation.

The chapter used several resource rent datasets available from the World Bank, and used the international commodity prices as an instrument to assure the direction of impact and avoid endogeneity.

One limitation of this chapter was the limited coverage of labour data provided by the International Labour Office (ILO). The data is scattered between the years and combines different surveys into the same dataset. While cleaning the data, I tried to choose the best combinations in order to establish homogeneous data series for each country that could provide reliable and feasible figures to the long panel used in this thesis. To overcome this limitation, I combined another labour dataset from UNIDO, despite its limited coverage on the manufacturing sector alone. Future research could try shortening the panel (smaller number of years) and obtain data from local surveys instead. The findings raised a question: if we know that the resource sectors are capital intensive and do not employ a large number of individuals, then where do resource-rich economies get concentrated? Also, what could be done to avoid this concentration trap? Analysis of these issues could be used to extend the research presented in this chapter.

Chapter 3 asked if institutional quality could have any role in determining the economic diversification when a country becomes oil abundant. The role of institutional quality on development and other aspects has been assessed in the literature thoroughly. However, the chapter contributes a new aspect for that role by looking at different economic diversification measures using an exogenous resource discovery variation. The primary finding was that countries respond differently to giant oil discoveries, as we aim to show that the quality of institutions determines whether countries avoid the resource curse or not. The combination of grabber-friendly institutions and giant oil discoveries leads to a less diversified economy in non-tradable sectors, whereas producer-friendly institutions help countries to take more advantage of these discoveries, and their following revenues, and maintain the employment share in manufacturing sector and tradables. However, producer-friendly institutions help countries to avoid export concentration: all countries tend to have concentrated exports with large shares in the resource sector.

A limitation of this chapter is the measure of institutional quality. The best available measure was “Polity2” from the “Polity IV” dataset, which gives a score from -10 to 10 to measure democracy in most countries in our sample and covers all the years up to 2012. The other available institutional quality measures do not report scores for sufficient number of years or even a wide range of countries as in our panel. Future research could address this issue, if more institutional quality measures could be developed.

Chapter 4 examined the Dutch Disease phenomena following resource booms, by testing the impact within the manufacturing sector industries and their exportability in both developing and developed countries. A main contribution of this chapter is to empirically examine the impact of two different oil booms on manufacturing across countries with a long panel, as previous literature has thoroughly examined that impact theoretically with only few empirical studies. In contrast to recent studies, the results emphasise the negative impact of oil booms on the tradable industries of manufacturing. A major difference in that chapter from previous recent studies is the scope of countries included in the panel: most recent studies only included limited numbers of countries (or even one country) or short time periods.

A challenging limitation of this chapter is that the UNIDO data does not cover any activities in the informal sector and microenterprises, which are often excluded from local industrial surveys. Therefore, the results are only applied on the organised formal parts of manufacturing. Future research could benefit from more data and surveys available, especially within the developing countries where the informal sector represents a bigger share of the economy.

The resource curse literature shows that some countries with high resource dependency have a successful experience in diversifying their exports and local economies. But many countries did not have this successful experience. The question that resource countries need to ask is how serious do they want to diversify their economies away from their natural resources and whether they were ready to move forward and take the necessary bold steps to achieve this goal. There are a number of policy implications that arise from the successful experiences to the remaining resource-countries (Gelb, 2011). First, it is critical to get the basic macroeconomic fundamentals right. For example, it is very important to run a successful countercyclical fiscal policy to contain the boom-bust cycles. Trade policy needs to be reasonably open in order to keep the local prices low amid increasing domestic rents. Second, it is vital to build other types of capital along with natural resource wealth, such as human capital and institutional capital. The literature shows that countries with less of these types of capital have higher exposure to the resource curse. Third, production costs in the newly targeted traded sectors must be lowered in order to support new entry and promote efficiency.

All of the successful resource-rich countries have used such vertical policies, with many of them increasing the range of exports and exploring new local business opportunities. Nevertheless, diversification is a national long-term priority, and natural resource rents should provide the governments with the needed financing to apply these vertical policies to achieve diversification in the long run.

The resource curse literature has developed in the past few years to empirically show that resource discoveries might actually be a blessing to the economy by showing a positive impact on real income. This thesis challenges these suggestions. The empirical evidence in this thesis demonstrates the long-term impact on the economic diversification, and on the manufacturing tradable industries, and finds a negative causal impact on these aspects. The resource-rich countries might benefit from resource booms in terms of higher income per capita, higher government revenues and higher local demand. What this thesis suggests is that even if income rises – as suggested by the literature – the long-term impact on the tradable industries is negative. Better institutions might help have better outcome in the local economy (measured by labour market diversification) but cannot help keeping the exports as diversified as other non-resource countries institutions do. The area of empirical studies in that field is still underdeveloped, and brings many avenues for future thorough research.

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Appendix A: Appendix to Chapter 2

Data description

1. Employment data

Sectoral employment data are from International Labour Office (ILO, 2013) and United Nations Industrial Development Organisation (UNIDO, 2012). ILO data covers 127 countries, while UNIDO covers 125 countries. The ILO data includes all economic activities at the 1-digit level between 1969 and 2008. Sectoral shares are in percentages. The unbalanced panel has 2369 observations (country-year). The ILO dataset reports employment in different classifications: some countries use the ISIC-revision 2, others moved to ISIC-revisions 3 and 4 in recent years, and some are using their own national classification. Employment data in the more disaggregated ISICrev3 and ISICrev4 were aggregated to ISICrev2, following Imbs and Wacziarg (2003), Timmer and Vries (2007) and McMillan and Rodrik (2011). If a country reports two revisions, the lower one is used. Official estimates are preferred over labour surveys. Data not following ISIC conventions are dropped. Table A-1 shows the concordance between ISICrev3 and ISICrev2.

Table A-1: different classifications between ISIC revisions 2 and 3*

ISIC-Revision 2	ISIC-Revision 3 Equivalent
1. Agriculture, Hunting, Forestry and Fishing	A. Agriculture, Hunting and Forestry B. Fishing
6. Wholesale and Retail Trade and Restaurants and Hotels	G. Wholesale and Retail Trade; Repair of Motor Vehicles, Motorcycles and Personal and Household Goods H. Hotels and Restaurants
8. Financing, Insurance, Real Estate and Business Services	J. Financial Intermediation K. Real Estate, Renting and Business Activities
9. Community, Social and Personal Services	L. Public Administration and Defence; Compulsory Social Security M. Education N. Health and Social Work O. Other Community, Social and Personal Service Activities P. Households with Employed Persons

* McMillan and Rodrik (2011) and Timmer and Vries (2007)

ILO data sometimes have sudden big changes in numbers in certain sectors, as countries sometimes change their calculation method, even if the same classification/revision is used. This is taken into consideration in this study, by dropping the observations that reports these sudden changes, making the panel more harmonised.

Our alternative data source is UNIDO, which covers manufacturing activities only at the 3-digit level of disaggregation (the main 23 industrial sectors) between 1963 and 2010 (INDSTAT2). (INDSTAT4 disaggregates to 4-digit level but only goes back to 1985.) The UNIDO dataset is consistent over the years and did not need adjustment. The unbalanced panel has 3564 employment observations (country-year).

2. Value added and labour productivity

The UNIDO dataset also provides information on value added per sector, offering an additional measure of sector size and productivity in industrial employment. The value added dataset covers almost the same period as the employment dataset, although some countries do not report the two sets equally. The unbalanced panel has 3465 added-value observations (country-year).

3. Exports data

Exports data are from the World Integrated Trade Solution (WITS), which is a collaboration between the World Bank and the United Nations Conference of Trade and Development (UNCTAD). The export data covers 133 countries. Data is selected in SITC-1-digit aggregation containing the main 10 trade sectors. Values are reported in constant 1000 USD with the base year being 2000. The unbalanced panel has 4575 observations (country-year). The WITS data values are consistent over the years and did not need any adjustment.

4. Diversification indicators

Computing these measures is done through Stata.[25]

Table A-2: The main differences between the chosen concentration measures[26].

Index	Distance Concept	Decomposable?	Independence of input scale & population size?	Range in interval [0,1]?
Gini	Depends on rank ordering	No	Yes	Yes
Theil	Proportional	Yes	Yes	No
HHI	Absolute differences	Yes	No: decreases with population	Yes: but min>0

We calculate diversity for all sectors, and for all non-resource sectors. Specifically, in the ILO data, we exclude "Mining and Quarrying," and in the WITS exports data we exclude "Crude material, inedible, except fuels," "Mineral Fuels, lubricants and related materials" and "Commodities not classified according to kind." The UNIDO data does not cover resource sectors at all.

Table A-3 shows summary statistics for the diversification measures used in this study. Table A-4 reports correlation between these measures, which is high. Figures A-1 to A-

25 Azevedo, João Pedro, (2007), AINEQUAL: Stata module to compute measures of inequality.
26 Cowell (2011)

6 in the appendices show the historical performance of the diversification using the Gini index in all sectors examined.

5. Natural resources data

Several natural resources are used in this study: oil, gas, nickel, tin, copper, gold, iron, forests, coal, bauxite, silver, lead and phosphate. Resource rents are from the World Bank Wealth of Nations Dataset and covers the period 1970 to 2008. Aggregate resource rent is calculated as the sum of all reported resources. The World Bank calculates resource rents as:

Rents=Unit rent*production

Unit rent=unit price-unit cost

All rents are reported in current US dollars.

The measure for resource rents used in this study is the log of resource rents per capita. Resource rents are available for a wide panel of countries for a long period of time, allowing testing long-term effects on diversification and minimising the risk of sample selection bias. Normalisation by population size, taken from the Penn World Tables, avoids a bias towards large countries. Several resources are aggregated, using data constructed using the same methodology, allowing us to examine the effect of different resources rents on diversification at the same time. This measure has been used by several recent studies (Bhattacharyya & Collier, 2011; Ross, 2006).

Table A-3: summary statistics for the sectoral concentration indices

Variable	Obs	Mean	Standard Deviation (Overall)	Standard Deviation (between countries)	Standard Deviation (within countries)	Min.	Max.
			ILO Employment Variables (all sectors)				
Gini	2369	0.5028	0.0787	0.0919	0.0374	0.2540	0.8329
Theil Index	2369	0.4971	0.2230	0.2464	0.1360	0.1044	2.5860
HHI	2369	0.2273	0.0753	0.1004	0.0348	0.1562	0.9999
			ILO Employment Variables (non-resource sectors)				
Gini	2369	0.4524	0.0877	0.1023	0.0413	0.2540	0.8132
Theil Index	2369	0.4002	0.2094	0.2409	0.1175	0.1044	2.0630
HHI	2368	0.2307	0.0751	0.1011	0.0337	0.1590	0.8136
			WITS Export Diversification Variables (all sectors)				
Gini	4577	0.6531	0.1286	0.1168	0.0652	0.3132	0.9
Theil Index	4576	0.9828	0.8018	0.6537	0.4968	0.1731	23.025
HHI	4554	0.3683	0.2059	0.1904	0.0950	0.1327	1
			WITS Export Diversification Variables (non-resource sectors)				
Gini	4575	0.6243	0.1139	0.0997	0.0658	0.3077	0.8888
Theil Index	4574	0.8708	0.9329	0.6555	0.6931	0.1631	19.775
HHI	4558	0.3440	0.1590	0.1388	0.0901	0.1435	1
			UNIDO Manufacturing Employment Variables (employment)				
Gini	3564	0.5087	0.1086	0.1109	0.0435	0.2886	0.8823
Theil Index	3564	0.5313	0.3302	0.4064	0.1397	0.1482	3.0334
HHI	3558	0.1345	0.0850	0.1016	0.0280	0.0612	0.8742
			UNIDO Manufacturing Employment Variables (Added Value)				
Gini	3465	0.6189	0.1151	0.1108	0.0470	0.3696	0.9321
Theil Index	3465	1.1910	1.2741	1.164	0.7014	0.2352	18.045
HHI	2473	0.1370	0.0788	.0791	.0348	0	0.6234
			Independent Variables				
Resource Rents Per Capita	8202	3.04e+08	1.72e+09	1.35e+09	1.18e+09	0	3.92e+10
GDP per Capita	8160	10138.92	50980.34	18753.4	47841.88	132.825	4095673

Notes: (ILO) data covers the years 1969-2008 (1-digit), the World Integrated Trade Solution (WITS, World Bank) data covering the years 1962-2012 (1-digit), and the United Nations Industrial Development Organisation (UNIDO) data covering the years 1963-2010 (3-digit). Resource rent per capita is calculated from resource rents (World Bank) and population (PWT 8.0). The Data Appendix provides detailed definition and source of the key variables used. The main index used in this paper is Gini; however, the other indices are also used and report similar results, as the next table shows high correlation.

Table A-4: Correlation matrices for the sectoral concentration indices

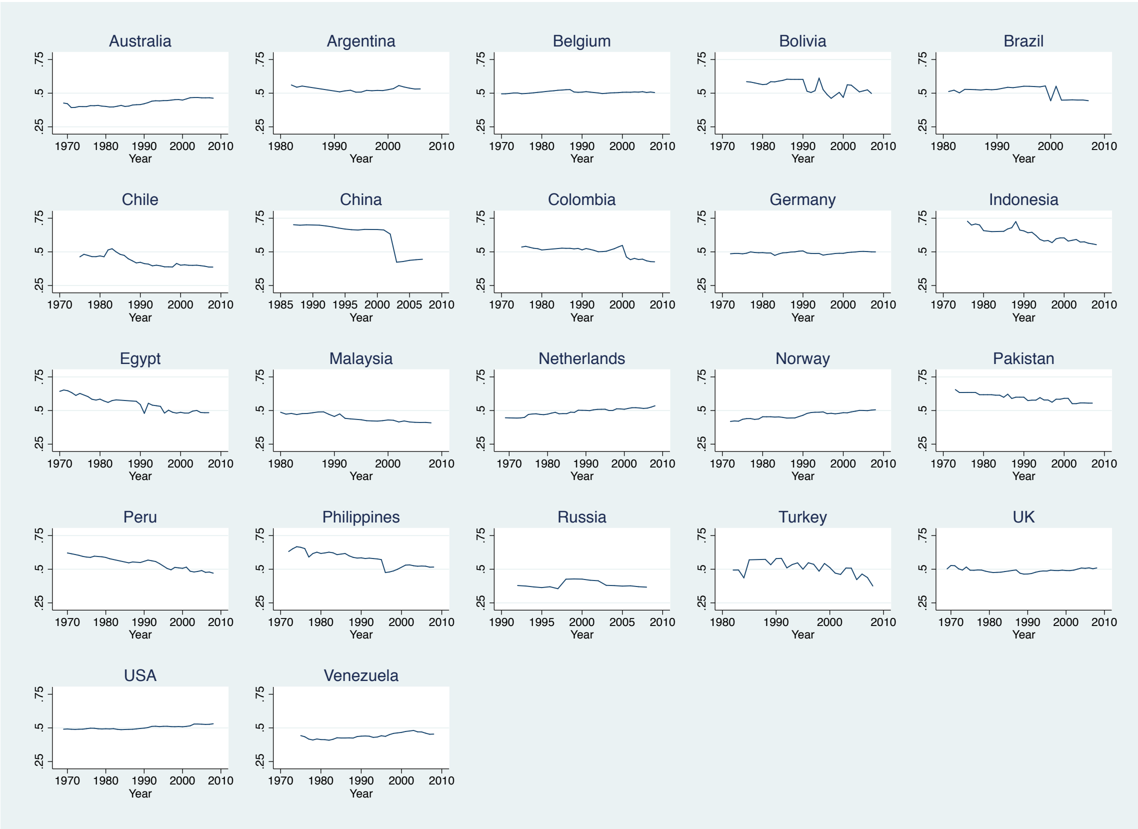
	Gini	Theil Index	HHI
ILO Employment Variables (all			
Gini	1.000		
Theil Index	0.897	1.000	
HHI	0.906	0.853	1.000
ILO Employment Variables (non-resource sectors)			
Gini	1.000		
Theil Index	0.932	1.000	
HHI	0.926	0.917	1.000
WITS Export Diversification Variables (all sectors)			
Gini	1.000		
Theil Index	0.741	1.000	
HHI	0.897	0.802	1.000
WITS Export Diversification Variables (non-Resource sectors)			
Gini	1.000		
Theil Index	0.677	1.000	
HHI	0.894	0.745	1.000
UNIDO Manufacturing Employment Variables (employment figures)			
Gini	1.000		
Theil Index	0.906	1.000	
HHI	0.727	0.803	1.000
UNIDO Manufacturing Employment Variables (Added Value)			
Gini	1.000		
Theil Index	0.678	1.000	
HHI	0.863	0.781	1.000

Table A-5: List of countries included in the sample, not all specifications cover the same number of countries due to data limitations:

Country	Oil producer	Net oil exporter	Oil Discoveries	Resource rent receiver	ILO 1969-2008	WITS 1962-2012	UNIDO 1963-2010
Afghanistan	x		x	x			
Albania	x		x	x	x	x	x
Algeria	x		x	x	x	x	x
Angola	x		x	x	x	x	x
Argentina	x		x	x	x	x	x
Armenia		x		x	x	x	x
Australia	x		x	x	x	x	x
Austria	x			x	x	x	x
Azerbaijan	x		x	x	x	x	x
Bahrain	x			x	x	x	
Bangladesh	x		x	x	x	x	x
Barbados	x			x	x		x
Belarus	x			x	x	x	x
Belgium		x		x	x	x	x
Benin	x			x	x	x	x
Bolivia	x		x	x	x	x	x
Bosnia and		x		x		x	x
Botswana		x		x	x	x	x
Brazil	x		x	x	x	x	x
Brunei Darussalam	x		x	x	x	x	
Bulgaria	x			x	x	x	x
Cameroon	x		x	x	x	x	x
Canada	x		x	x	x	x	x
Chile	x			x	x	x	x
China	x		x	x	x	x	x
Colombia	x		x	x	x	x	x
Congo, Dem. Rep.	x			x	x	x	
Congo, Rep.	x		x	x	x	x	x
Costa Rica		x		x	x	x	x
Cote d'Ivoire	x		x	x	x	x	x
Croatia	x			x	x	x	x
Cuba	x			x	x	x	x
Cyprus		x		x	x	x	x
Czech Republic	x			x	x	x	x
Denmark	x		x	x	x	x	x
Dominican Republic		x		x	x	x	x
Ecuador	x		x	x	x	x	x
Egypt, Arab Rep.	x		x	x	x	x	x
El Salvador		x		x	x	x	x
Equatorial Guinea			x	x			
Eritrea		x		x		x	
Estonia		x		x	x	x	
Ethiopia		x		x	x	x	
Finland		x		x	x	x	x
France	x		x	x	x	x	x
Gabon	x		x	x	x	x	x
Georgia	x			x	x	x	x
Germany	x		x	x	x	x	x
Ghana	x			x	x	x	x
Greece	x			x	x	x	x
Guatemala	x			x	x	x	x
Haiti		x		x	x	x	x
Honduras		x		x	x	x	x
Hong Kong SAR,		x		x	x	x	x
Hungary	x		x	x	x	x	x
Iceland		x			x	x	x
India	x		x	x		x	x
Indonesia	x		x	x	x	x	x
Iran, Islamic Rep.	x		x	x	x	x	x
Iraq	x		x	x	x	x	x
Ireland		x		x	x	x	x
Israel	x			x	x	x	x
Italy	x		x	x	x	x	x
Jamaica		x		x	x	x	x
Japan	x			x	x	x	x
Jordan	x			x	x	x	x
Kazakhstan	x		x	x	x	x	x
Kenya		x		x		x	x
Korea, Rep.		x		x	x	x	x
Kuwait	x		x	x	x	x	x

Kyrgyz Republic	x			x	x	x	x
Latvia		x		x	x	x	x
Lebanon		x				x	x
Libya	x		x	x	x	x	x
Lithuania	x			x	x	x	x
Luxembourg		x			x	x	x
Macedonia, FYR		x		x	x	x	x
Malaysia	x			x	x	x	x
Malta		x			x	x	x
Malaysia	x	x	x	x	x	x	x
Mexico	x		x	x	x	x	x
Moldova	x			x	x	x	x
Mongolia	x			x	x	x	x
Montenegro		x			x	x	
Morocco	x		x	x	x	x	x
Mozambique		x		x		x	x
Myanmar	x		x	x	x	x	x
Namibia		x	x	x	x	x	
Nepal		x		x	x	x	x
Netherlands	x		x	x	x	x	x
New Zealand	x		x	x	x	x	x
Nicaragua		x		x	x	x	x
Nigeria	x		x	x	x	x	x
Norway	x		x	x	x	x	x
Oman	x		x	x	x	x	x
Pakistan	x		x	x	x	x	x
Panama		x			x	x	x
Papua New Guinea	x		x	x	x	x	x
Paraguay		x			x	x	x
Peru	x		x	x	x	x	x
Philippines	x		x	x	x	x	x
Poland	x			x	x	x	x
Portugal		x		x	x	x	x
Qatar	x		x	x	x	x	x
Romania	x		x	x	x	x	x
Russian Federation	x		x	x	x	x	x
Saudi Arabia	x		x	x	x	x	x
Senegal	x			x	x	x	x
Serbia	x				x	x	x
Singapore		x			x	x	x
Slovak Republic	x			x	x	x	x
Slovenia	x			x	x	x	x
South Africa	x			x	x	x	x
Spain	x		x	x	x	x	x
Sri Lanka		x		x	x	x	x
Suriname	x			x	x		x
Sudan	x		x	x	x	x	x
Sweden	x			x	x	x	x
Switzerland		x		x	x	x	x
Syrian Arab Republic	x		x	x	x	x	x
Tajikistan	x			x	x	x	x
Tanzania		x		x	x	x	x
Thailand	x		x	x	x	x	x
Togo		x		x		x	
Trinidad and Tobago	x		x	x	x	x	x
Tunisia	x		x	x	x	x	x
Turkey	x			x	x	x	x
Turkmenistan	x		x	x	x	x	
Ukraine	x			x	x	x	x
United Arab Emirates	x		x	x	x	x	x
United Kingdom	x		x	x	x	x	x
United States	x		x	x	x	x	x
USSR			x				
Uruguay		x		x		x	x
Uzbekistan	x			x	x		
Venezuela, RB	x		x	x	x	x	x
Vietnam	x		x	x	x	x	x
Yemen, Rep.	x		x	x	x	x	x
Zambia		x		x	x	x	x
Zimbabwe		x		x		x	x

Figure A-1: Aggregate structural change across countries since 1969



Note: Aggregate structural change (or internal diversification) here is measured by Gini coefficient for the inequality of sector shares in employment. Higher Gini implies diversification concentration and vice versa. Aggregate implies that the figure includes both resource and non-resource sectors. The data is sourced from ILO.

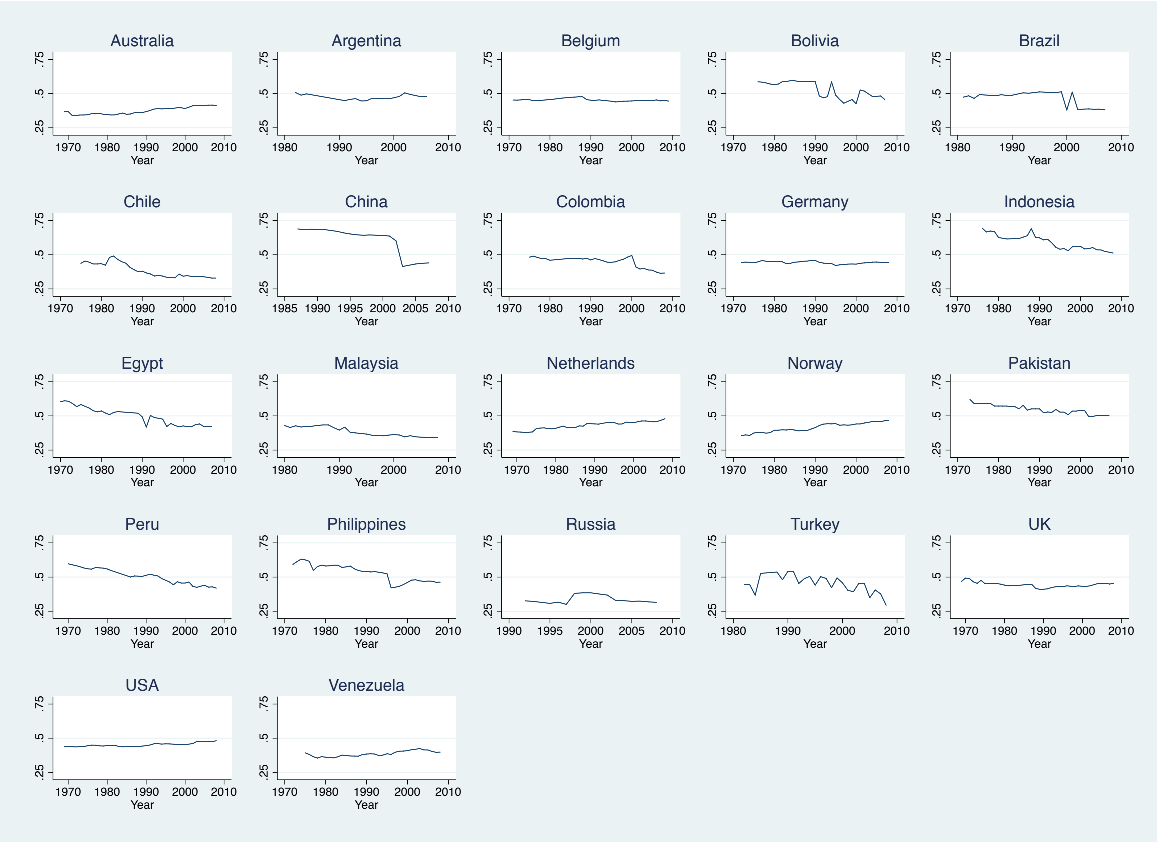
Figure A-2: Structural change in manufacturing across countries measured by Gini since 1963

Note: Structural change (or internal diversification) within manufacturing here is measured by Gini coefficient for the inequality of sector shares in employment. Higher Gini implies concentration and vice versa. The data is sourced from UNIDO.

Figure A-3: Structural change in manufacturing value added across countries measured by Gini since 1963

Note: Structural change (or internal diversification) in manufacturing here is measured by Gini coefficient for the inequality of sector shares in value added. Higher Gini implies concentration and vice versa. The data is sourced from UNIDO.

Figure A-4: Structural change within non-resource sectors measured by Gini since 1969



Note: Structural change (or internal diversification) within non-resource sectors here is measured by Gini coefficient for the inequality of sector shares in employment. Higher Gini implies concentration and vice versa. The data is sourced from ILO.

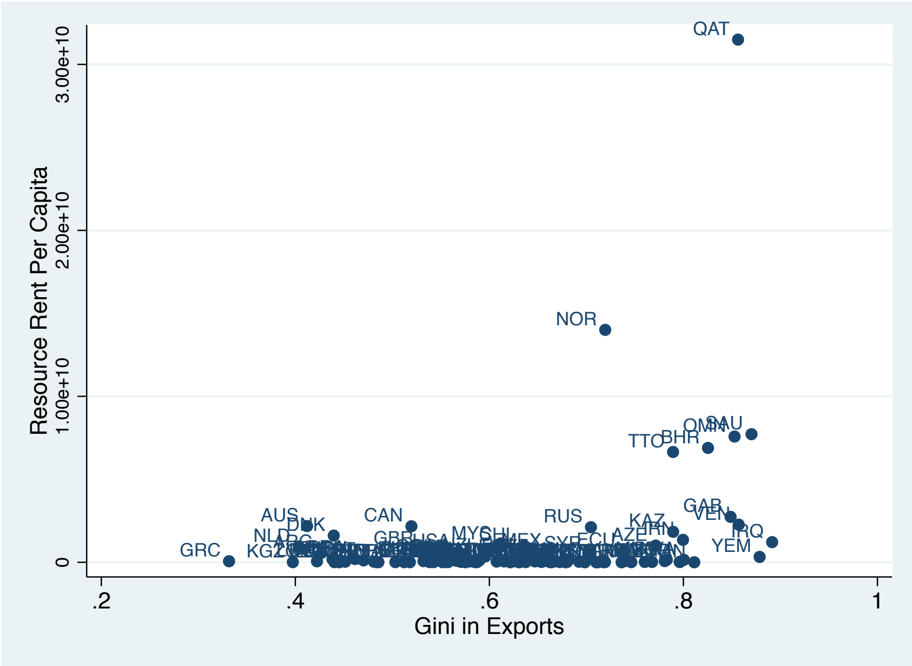
Figure A-5: Export diversification across countries measured by Gini since 1962

Note: Aggregate export diversification here is measured by Gini coefficient for the inequality of sector shares in exports. Higher Gini implies concentration and vice versa. The data is sourced from WITS.

Figure A-6: Export diversification in non-resource sectors across countries measured by Gini since 1962

Note: Export diversification in the non-resource sector here is measured by Gini coefficient for the inequality of sector shares in exports. Higher Gini implies concentration and vice versa. The data is sourced from WITS.

Figure A-7: Export Diversification and Resource Rents Per Capita across countries



Note: Countries with higher resource rents per capita also have the highest concentration (Gini) in exports.

Appendix B: Appendix to Chapter 3

Table B-1: summary statistics for the sectoral concentration indices

Variable	Obs	Mean	Standard Deviation (Overall)	Standard Deviation (between countries)	Standard Deviation (within countries)	Min.	Max.
			ILO Employment Variables (all sectors)				
Gini	2369	0.5028	0.0787	0.0919	0.0374	0.2540	0.832
Theil Index	2369	0.4971	0.2230	0.2464	0.1360	0.1044	2.586
HHI	2369	0.2273	0.0753	0.1004	0.0348	0.1562	0.999
			ILO Employment Variables (non-resource sectors)				
Gini	2369	0.4524	0.0877	0.1023	0.0413	0.2540	0.813
Theil Index	2369	0.4002	0.2094	0.2409	0.1175	0.1044	2.063
HHI	2368	0.2307	0.0751	0.1011	0.0337	0.1590	0.813
			WITS Export Diversification Variables (all sectors)				
Gini	4577	0.6531	0.1286	0.1168	0.0652	0.3132	0.9
Theil Index	4576	0.9828	0.8018	0.6537	0.4968	0.1731	23.02
HHI	4554	0.3683	0.2059	0.1904	0.0950	0.1327	1
			WITS Export Diversification Variables (non-resource sectors)				
Gini	4575	0.6243	0.1139	0.0997	0.0658	0.3077	0.888
Theil Index	4574	0.8708	0.9329	0.6555	0.6931	0.1631	19.77
HHI	4558	0.3440	0.1590	0.1388	0.0901	0.1435	1
			UNIDO Manufacturing Employment Variables (employment)				
Gini	3564	0.5087	0.1086	.1109	.0435	0.2886	0.882
Theil Index	3564	0.5313	0.3302	.4064	.1397	0.1482	3.033
HHI	3558	0.1345	0.0850	.1016	.0280	0.0612	0.874
			UNIDO Manufacturing Employment Variables (Added Value)				
Gini	3465	0.6189	0.1151	.1108	.0470	0.3696	0.932
Theil Index	3465	1.1910	1.2741	1.164	.7014	.2352	18.04
HHI	2473	0.1370	0.0788	.0791	.0348	0	0.623
			Other Variables				
Oil discoveries	8933	0.0499	0.2178	0.1159	0.1843	0	1
Services GDP	5675	106e+11	5.02e+11	4.90e+11	1.57e+11	-3799643	8.64e+12
Manufacturing GDP	5072	2.45e+1	1.09e+11	1.52e+11	1.76e+10	164035.8	1.79e+12

Table B-2: Correlation matrices for the sectoral concentration indices

	Gini	Theil	HHI
ILO Employment variables (all sectors)			
Gini	1.000		
Theil Index	0.897	1.000	
HHI	0.906	0.853	1.000
WITS Export Diversification Variables (all sectors)			
Gini	1.000		
Theil Index	0.741	1.000	
HHI	0.897	0.802	1.000
UNIDO Manufacturing Employment Variables (employment figures)			
Gini	1.000		
Theil Index	0.906	1.000	
HHI	0.727	0.803	1.000

Table B-3: Effect of other non-giant oilfield discovery on diversification

Outcome variable					
Diversification in:	**t+2**	**t+4**	**t+6**	**t+8**	**t+10**
Panel A. Exports					
Discovery	-0.006	-0.007	0.003	0.013**	0.011*
	(0.006)	(0.006)	(0.005)	(0.006)	(0.006)
Past discoveries	-0.006***	-0.006***	-0.007***	-0.008***	-0.008***
	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)
Observations	3677	3889	3971	3936	3900
Panel B. Sectoral employment					
Discovery	-0.000	-0.000	0.004	0.001	-0.003
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Past discoveries	-0.004***	-0.004***	-0.004***	-0.004***	-0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	2049	2191	2232	2205	2178
Panel C. Manufacturing employment					
Discovery	-0.001	0.004	0.002	-0.004	-0.004
	(0.003)	(0.004)	(0.004)	(0.003)	(0.003)
Past discoveries	0.000	-0.000	0.000	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	3120	3244	3289	3263	3235

Notes: Standard errors are in parentheses. All regressions include previous discoveries over the past ten years, country and year fixed effects. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B-4: Effect of giant oil discovery size on diversification

Outcome variable *Diversification in:*	t+2	t+4	t+6	t+8	t+10
Panel A. Discovery size in quartile 1					
Exports	-0.008	-0.014	-0.003	0.004	0.016*
	(0.010)	(0.011)	(0.009)	(0.009)	(0.009)
Sectoral Employment	0.003	0.010	0.008	-0.001	-0.001
	(0.007)	(0.006)	(0.006)	(0.007)	(0.007)
Manufacturing Emp.	0.001	0.004	0.001	-0.002	-0.008*
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Manufacturing VA	-0.003	-0.002	-0.003	-0.004	-0.004
	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)
Panel B. Discovery size in quartile 2					
Exports	-0.007	-0.004	0.002	0.009	0.004
	(0.008)	(0.010)	(0.009)	(0.009)	(0.009)
Sectoral Employment	-0.002	-0.003	0.003	0.011*	-0.002
	(0.006)	(0.007)	(0.006)	(0.006)	(0.006)
Manufacturing Emp.	-0.010*	-0.004	-0.002	-0.009*	-0.009*
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Manufacturing VA	0.003	-0.002	0.003	-0.001	-0.001
	(0.007)	(0.007)	(0.006)	(0.006)	(0.005)
Panel C. Discovery size in quartile 3					
Exports	0.001	-0.000	0.004	0.006	0.000
	(0.010)	(0.010)	(0.010)	(0.010)	(0.009)
Sectoral Employment	-0.005	-0.008	0.000	-0.004	-0.001
	(0.007)	(0.009)	(0.007)	(0.008)	(0.007)
Manufacturing Emp.	0.003	0.005	0.000	-0.006	0.003
	(0.007)	(0.006)	(0.006)	(0.006)	(0.005)
Manufacturing VA	0.006	0.002	0.004	-0.008	-0.011*
	(0.007)	(0.008)	(0.007)	(0.007)	(0.006)
Panel D. Discovery size in quartile 4					
Exports	-0.003	0.005	0.012	0.023***	0.013
	(0.012)	(0.010)	(0.009)	(0.009)	(0.010)
Sectoral Employment	0.004	-0.009	-0.009	-0.006	-0.005
	(0.008)	(0.012)	(0.011)	(0.007)	(0.007)
Manufacturing Emp.	0.008	0.009	0.009	0.009	0.005
	(0.009)	(0.008)	(0.008)	(0.008)	(0.007)
Manufacturing VA	0.015**	0.002	-0.002	0.012*	0.006
	(0.007)	(0.007)	(0.006)	(0.006)	(0.009)

Notes: Standard errors are in parentheses. All regressions include previous discoveries over the past ten years, country and year fixed effects. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

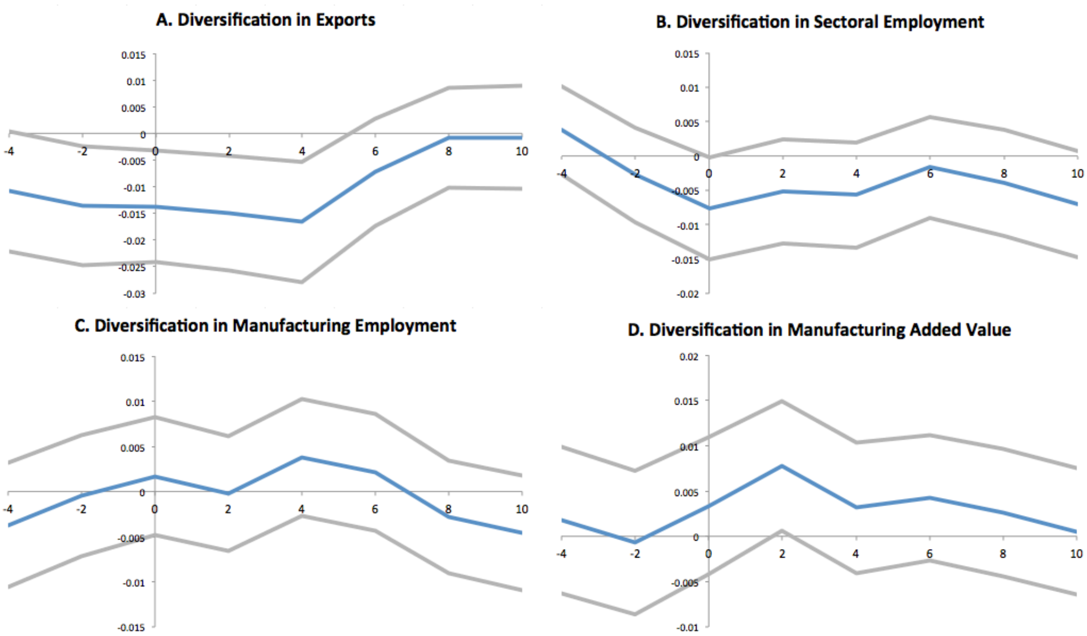
Table B-5: Countries and type of government at time of discovery

Democratic	**Autocratic**
Argentina	Afghanistan
Australia	Albania
Bolivia	Algeria
Brazil	Argentina
Canada	Azerbaijan
Colombia	Bangladesh
Congo, Rep	Brazil
Denmark	Cameron
Ecuador	China
France	Colombia
India	Congo, Rep
Indonesia	Cote d'Ivoire
Iran	Egypt
Italy	Equatorial Guinea
Malaysia	Gabon
Mexico	Hungary
Netherlands	Indonesia
New Zealand	Iran
Nigeria	Iraq
Norway	Kazakhstan
Pakistan	Kuwait
Papua New Guinea	Libya
Peru	Mexico
Philippines	Morocco
Romania	Myanmar
Russia	Nigeria
Spain	Oman
Thailand	Qatar
Trinidad & Tobago	Saudi Arabia
United Kingdom	Sudan
United States	Thailand
Venezuela	Tunisia
	Turkmenistan
	USSR
	United Arab Emirates
	Venezuela
	Vietnam

Table B-6: Countries with two types of government in the year prior to a giant oil discovery

Country	Discovery year	Type of government (polity2)	Country	Discovery year	Type of government (polity2)
Argentina	1971	Autocratic (-9)	Mexico	1951	Autocratic (-6)
	1977	Autocratic (-9)		1952	Autocratic (-6)
	1989	Democratic (8)		1958	Autocratic (-6)
	1996	Democratic (7)		1966	Autocratic (-6)
Brazil	1965	Autocratic (-3)		1972	Autocratic (-6)
	1968	Autocratic (-8)		1975	Autocratic (-6)
	1972	Autocratic (-9)		1976	Autocratic (-6)
	1984	Autocratic (-3)		1977	Autocratic (-6)
	1985	Autocratic (-3)		1979	Autocratic (-3)
	1987	Democratic (7)		1980	Autocratic (-3)
	1989	Democratic (7)		1982	Autocratic (-3)
	1993	Democratic (8)		1990	Autocratic (0)
	1996	Democratic (8)		1998	Democratic (6)
	1999	Democratic (8)	Nigeria	1958	NA
	2001	Democratic (8)		1959	NA
	2002	Democratic (8)		1962	Democratic (8)
	2003	Democratic (8)		1963	Democratic (8)
Colombia	1956	Autocratic (-5)		1964	Democratic (8)
	1973	Democratic (7)		1965	Democratic (7)
	1992	Democratic (9)		1967	Autocratic (-7)
	1993	Democratic (9)		1968	Autocratic (-7)
Congo, Rep	1969	Autocratic (-7)		1970	Autocratic (-7)
	1971	Autocratic (-7)		1973	Autocratic (-7)
	1983	Autocratic (-8)		1981	Democratic (7)
	1995	Democratic (5)		1989	Autocratic (-7)
Indonesia	1969	Autocratic (-7)		1990	Autocratic (-5)
	1970	Autocratic (-7)		1996	Autocratic (-6)
	1971	Autocratic (-7)		1998	Autocratic (-7)
	1972	Autocratic (-7)		1999	Autocratic (-1)
	1973	Autocratic (-7)		2000	Democratic (4)
	1974	Autocratic (-7)		2001	Democratic (4)
	1982	Autocratic (-7)		2002	Democratic (4)
	1991	Autocratic (-7)	Thailand	1973	Autocratic (-7)
	1994	Autocratic (-7)		1980	Democratic (2)
	1995	Autocratic (-7)		1995	Democratic (9)
	1996	Autocratic (-7)	Venezuela	1954	Autocratic (-3)
	1997	Autocratic (-7)		1955	Autocratic (-3)
	1999	Autocratic (-5)		1957	Autocratic (-3)
	2000	Democratic (6)		1958	Autocratic (-3)
Iran	1958	Autocratic (-10)		1979	Democratic (9)
	1960	Autocratic (-10)		1980	Democratic (9)
	1961	Autocratic (-10)		1986	Democratic (9)
	1962	Autocratic (-10)		1988	Democratic (9)
	1963	Autocratic (-10)		1999	Democratic (8)
	1964	Autocratic (-10)		2002	Democratic (6)
	1965	Autocratic (-10)			
	1966	Autocratic (-10)			
	1967	Autocratic (-10)			
	1968	Autocratic (-10)			
	1969	Autocratic (-10)			
	1972	Autocratic (-10)			
	1973	Autocratic (-10)			
	1974	Autocratic (-10)			
	1975	Autocratic (-10)			
	1976	Autocratic (-10)			
	1978	Autocratic (-10)			
	1980	Autocratic (0)			
	1988	Autocratic (-6)			
	1991	Autocratic (-6)			
	1992	Autocratic (-6)			
	1993	Autocratic (-6)			
	1994	Autocratic (-6)			
	1995	Autocratic (-6)			
	1999	Democratic (3)			
	2000	Democratic (3)			
	2001	Democratic (3)			

Figure B-1: Impact of giant oilfield discovery on diversification in exports, in sectoral employment, in manufacturing employment and value added; these regressions do not control for previous discoveries



Notes: The x-axes report the number of years before or after t, ranging from t-4 to t+10. The purple lines show the estimated coefficients and the grey lines show the 95% confidence intervals based on robust standard errors, which are clustered by country. All regressions control for real GDP and include country and year fixed effects. Details on variable construction can be found in the data section of the paper.

Employment data

Sectoral employment data are from International Labour Office (ILO, 2013) and United Nations Industrial Development Organisation (UNIDO, 2012). ILO data covers 127 countries, while UNIDO covers 125 countries. The ILO data includes all economic activities at the 1-digit level between 1969 and 2008. Sectoral shares are in percentages. The unbalanced panel has 2369 observations (country-year). The ILO dataset reports employment in different classifications: some countries use the ISIC-revision 2, others moved to ISIC-revisions 3 and 4 in recent years, and some are using their own national classification. Employment data in the more disaggregated ISICrev3 and ISICrev4 were aggregated to ISICrev2, following Imbs and Wacziarg (2003), Timmer and de Vries (2008) and McMillan and Rodrik (2011). If a country reports two revisions, the lower one is used. Official estimates are preferred over labour surveys. Data not following ISIC conventions are dropped. Table B-7 shows the concordance between ISICrev3 and ISICrev2.

ILO data sometimes have sudden big changes in numbers in certain sectors, as countries occasionally change their calculation method even if the same classification/revision is used. This is taken into consideration in this study, by dropping the observations that report these sudden changes, making the panel more harmonised.

Our alternative data source is UNIDO, which covers manufacturing activities only at the 3-digit level of disaggregation (the main 23 industrial sectors) between 1963 and 2010 (INDSTAT2). (INDSTAT4 disaggregates to 4-digit level but only goes back to 1985). The UNIDO dataset is consistent over the years and did not need adjustment. The unbalanced panel has 3564 employment observations (country-year).

Table B-7: different classifications between ISIC revisions 2 and 3*

ISIC-Revision 2	ISIC-Revision 3 Equivalent
1. Agriculture, hunting, forestry and fishing	A. Agriculture, hunting and forestry B. Fishing
6. Wholesale and retail trade and restaurants and hotels	G. Wholesale and retail trade; repair of motor vehicles, motorcycles and personal and household goods H. Hotels and restaurants
8. Financing, insurance, real estate and business services	J. Financial intermediation K. Real estate, renting and business activities
9. Community, social and personal services	L. Public administration and defence; compulsory social security M. Education N. Health and social work O. Other community, social and personal service activities P. Households with employed persons

* McMillan and Rodrik (2011) and Timmer and de Vries (2008)

Export data

Export data are from the World Integrated Trade Solution (WITS), which is a collaboration between the World Bank and the United Nations Conference of Trade and Development (UNCTAD). The export data covers 133 countries. Data is selected in SITC-1-digit aggregation containing the main 10 trade sectors. Values are reported in constant 1000 USD, with base year 2000. The unbalanced panel has 4575 observations (country-year). The WITS data values are consistent over the years and did not need any adjustment.

Diversification indicators

Computing these measures is done through Stata.[27]

Table B-8: The main differences between the chosen concentration measures[28]

Index	Distance Concept	Decomposable?	Independence of input scale and population size?	Range in interval [0,1]?
Gini	Depends on rank ordering	No	Yes	Yes
Theil	Proportional	Yes	Yes	No
HHI	Absolute differences	Yes	No: decreases with population	Yes: but min>0

We calculate diversity for all sectors and for all non-resource sectors. Specifically, in the ILO data, we exclude “mining and quarrying,” and in the WITS exports data we exclude “crude material, inedible, except fuels,” “mineral fuels, lubricants and related materials” and “commodities not classified according to kind.” The UNIDO data does not cover resource sectors at all.

27 Azevedo, João Pedro, (2007), AINEQUAL: Stata module to compute measures of inequality.

28 Cowell (2011).

Appendix C: Appendix to Chapter 4

Table C-1: Number of years (from 1962 to 2003) with one or more giant oilfield discoveries, by country (treatment countries)

Country	Years	Country	Years	Country	Years
Former USSR	29	India	5	Albania	1
Iran	24	Algeria	4	Azerbaijan	1
Saudi Arabia	24	Argentina	4	Bangladesh	1
Australia	18	Colombia	4	Cote d'Ivoire	1
Nigeria	17	Congo, Rep.	4	Denmark	1
China	16	Kuwait	4	Ecuador	1
United States	16	Qatar	4	Equatorial Guinea	1
Norway	15	Peru	3	France	1
Indonesia	14	Thailand	3	Gabon	1
Brazil	13	Tunisia	3	Germany	1
United Arab Emirates	12	Bolivia	2	Hungary	1
United Kingdom	12	Brunei Darussalam	2	Morocco	1
Iraq	11	Italy	2	Namibia	1
Libya	11	Kazakhstan	2	New Zealand	1
Mexico	10	Myanmar	2	Papua New Guinea	1
Egypt, Arab Rep.	8	Netherlands	2	Philippines	1
Oman	8	Pakistan	2	Romania	1
Angola	7	Sudan	2	Russia	1
Canada	7	Trinidad & Tobago	2	Spain	1
Malaysia	6	Vietnam	2	Turkmenistan	1
Venezuela	6	Yemen	2		

Table C-2: Manufacturing ISIC 2-digit industries from INDSTAT2-UNIDO

ISIC	Industrial sectors	Exportability 1	Exportability 2
15	Food and beverages	1	0
16	Tobacco products	0	0
17	Textiles	1	0
18	Wearing apparel	1	0
19	Leather products and footwear	1	0
20	Wood products except furniture	1	0
21	Paper and paper products	0	0
22	Printing and publishing	0	0
23	Coke, refined petroleum products and nuclear fuel	1	0
24	Chemicals and chemical products	1	0
25	Rubber and plastics products	0	0
26	Non-metallic mineral products	0	0
27	Basic metals	1	0
28	Fabricated metal products	0	0
29	Machinery and equipment	1	1
30	Office, accounting and computing machinery	1	1
31	Electrical machinery and apparatus	0	1
32	Radio, television and communication equipment	0	1
33	Medical, precision and optical instruments	1	1
34	Motor vehicles, trailers and semi-trailers	1	1
35	Other transport equipment	1	1
36	Furniture	0	0
37	Recycling	0	0

Table C-3: Real exchange rate appreciation, oil discoveries and oil rents as a share of GDP

	Dependent variable is:					
	(1)	(2)	(3)	(4)	(5)	(6)
	RER appreciation	**RER appreciation**	**RER appreciation**	**RER appreciation**	**Oil rent**	**RER appreciation**
Oil discovery	-0.026***					
	(0.006)					
Oil discovery (t+5)		-0.011**				
		(0.004)				
Oil discovery (t+8)			0.012***		2.6e+09***	
			(0.005)		(3.0e+08)	
Oil rent				0.000***		
				(0.000)		
Boom						1.145***
						(0.013)
Bust						0.869***
						(0.012)
Valley						0.985***
						(0.013)
Observations	148994	157757	57684	44735	66746	187542
R^2	0.65	0.63	0.68	0.61	0.62	0.60

Notes: all regressions include country, year and industry fixed effects. Robust standard errors clustered at the country level are reported in parenthesis. ***, ** and * denote significant at the 1, 5 and 10% level. Regressions (3) and (5) control for past discoveries: the number of years with discoveries from t-10 to t-1. Oil rent data is from the World Bank.

Table C-4: The impact of oil boom and bust on manufacturing outputs, including all oil countries in the dataset (oil-producing net importers included)

	Value added			Employment			Wages		
	All	Interacted* Exp index 1	Interacted* Exp index 2	All	Interacted* Exp index 1	Interacted* Exp index 2	All	Interacted* Exp index 1	Interacted* Exp index 2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Boom	-0.201***	0.007	-0.001	-0.070***	0.010**	0.013**	-0.182***	0.013**	0.006
	(0.012)	(0.007)	(0.009)	(0.010)	(0.005)	(0.006)	(0.011)	(0.006)	(0.008)
Bust	0.026**	-0.017*	-0.016	-0.064***	0.002	-0.011	-0.003	0.003	-0.014
	(0.012)	(0.009)	(0.012)	(0.008)	(0.006)	(0.008)	(0.011)	(0.008)	(0.011)
Valley	-0.060***	-0.008	-0.018	-0.075***	0.000	-0.015*	-0.070***	0.003	-0.024**
	(0.016)	(0.009)	(0.013)	(0.010)	(0.006)	(0.008)	(0.013)	(0.009)	(0.012)
Industry share (t-2)	-0.532***	-0.532***	-0.530***	-0.320***	-0.318***	-0.318***	-0.331***	-0.329***	-0.328***
	(0.054)	(0.054)	(0.054)	(0.028)	(0.028)	(0.028)	(0.034)	(0.034)	(0.034)
Obs	59319	59319	59319	67251	67251	67251	60861	60861	60861
R^2	0.053	0.053	0.053	0.052	0.052	0.052	0.089	0.089	0.089

Notes: all regressions include country, year and industry fixed effects. Robust standard errors clustered at the country level are reported in parenthesis. ***, ** and * denote significant at the 1, 5 and 10% level. Exportability index (1) is a dummy that takes on a value of 1 if an industry's ratio of exports to value added is greater than the median value and is 0 otherwise, from Rajan and Subramanian (2011). Exportability index (2) is a dummy that takes on a value of 1 for ISIC industries 15-21, and is 0 otherwise (author calculation). This table repeats Table 4-9 but we add Albania, Canada, Colombia, Egypt, Malaysia, Mexico and the United States in the regression, in addition to the countries included in the main regression shown in Table 4-9.

Table C-5: The impact of oil boom and bust on manufacturing outputs, breaking up the 2000's oil boom into two booms: boom3, 2002-2007; and boom4, 2009-2012

	Value added			Employment			Wages		
	All	Interacted * Exp index 1	Interacted * Exp index 2	All	Interacted * Exp index 1	Interacted * Exp index 2	All	Interacted * Exp index 1	Interacted * Exp index 2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Boom3	-0.064	-0.001	-0.049	-0.080**	-0.060***	-0.008	0.062	-0.015	-0.014
	(0.051)	(0.034)	(0.049)	(0.033)	(0.022)	(0.031)	(0.052)	(0.030)	(0.039)
Boom4	-0.088	0.012	0.028	-0.170***	0.008	0.050	-0.143**	0.037	0.061
	(0.070)	(0.073)	(0.109)	(0.060)	(0.060)	(0.065)	(0.061)	(0.053)	(0.071)
Bust	-0.128***	-0.031	-0.080*	-0.111***	-0.014	-0.017	-0.141***	-0.011	-0.059
	(0.048)	(0.030)	(0.042)	(0.031)	(0.017)	(0.024)	(0.037)	(0.028)	(0.037)
Valley	-0.088	0.020	0.005	-0.102***	-0.012	-0.004	-0.059	-0.014	-0.019
	(0.058)	(0.031)	(0.050)	(0.037)	(0.018)	(0.028)	(0.046)	(0.023)	(0.033)
Industry share (t-2)	-0.388***	-0.371***	-0.388***	-0.411***	-0.416***	-0.412***	-0.326***	-0.322***	-0.325***
	(0.094)	(0.091)	(0.094)	(0.061)	(0.061)	(0.061)	(0.075)	(0.076)	(0.076)
Obs	7680	7680	7680	8046	8046	8046	7709	7709	7709
R2	0.053	0.054	0.054	0.052	0.053	0.053	0.089	0.089	0.090

Notes: all regressions include country, year and industry fixed effects. Robust standard errors clustered at the country level are reported in parenthesis. ***, ** and * denote significant at the 1, 5 and 10% level. Exportability index (1) is a dummy that takes on a value of 1 if an industry's ratio of exports to value added is greater than the median value and is 0 otherwise, from Rajan and Subramanian (2011). Exportability index (2) is a dummy that takes on a value of 1 for ISIC industries 15-21, and is 0 otherwise (author calculation).

Table C-6: Oil discovery and the tradable industries, instrumenting the discovery variables following Cotet and Tsui (2013)

Outcome in year:	(1)	(2)
Panel A. Value added (t+5)		
Discovery*exportability 1	-0.121	
	(0.270)	
Discovery*exportability 2		-0.647
		(0.844)
Past discoveries	0.009	0.017
	(0.017)	(0.021)
Manufacturing share (t-1)	0.162**	0.177**
	(0.076)	(0.079)
Kleibergen-Paap F stat	25.88	17.75
Stock-yogo critical value	16.38/5.53	16.38/5.53
Observations	12416	12416
R^2	0.046	-0.019
Panel B. Employment (t+5)		
Discovery*exportability 1	-0.894	
	(2.189)	
Discovery*exportability 2		-3.140
		(7.252)
Past discoveries	0.051	0.075
	(0.129)	(0.178)
Manufacturing share (t-1)	-0.290**	-0.116
	(0.119)	(0.293)
Kleibergen-Paap F stat	0.288	0.313
Stock-yogo critical value	16.38/5.53	16.38/5.53
Observations	53060	53060
R^2	-0.330	-2.204
Panel C. Wages (t+10)		
Discovery*exportability 1	0.173	
	(0.222)	
Discovery*exportability 2		-0.489
		(0.878)
Past discoveries	-0.008	0.012
	(0.011)	(0.019)
Manufacturing share (t-1)	-0.232***	-0.213***
	(0.031)	(0.059)
Kleibergen-Paap F stat	27.70	1.303
Stock-yogo critical value	16.38/5.53	16.38/5.53
Observations	44370	44370
R^2	0.045	0.022

Notes: All regressions controls for the number of years with discoveries from t-10 to t-1, and country, industry and year fixed effects. Instrumental variable is the log (oil reserves per capita) and its interaction with exportability indices 1 and 2 for instrumenting the interaction term (Discovery*Exportability 1&2). Data sources: manufacturing employment is from UNIDO, and the instrument is from Cotet and Tsui (2013). Robust standard errors are in parentheses. * p <0.10, ** p < 0.05, *** p < 0.01

Table C-7: Oil discovery and the tradable industries using nominal figures for value added and wages

Outcome in year:	*j=0*	*j=5*			*j=10*		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Value Added							
Oil discovery (t+j)	0.003	-0.007			-0.018***		
	(0.007)	(0.007)			(0.007)		
Oil discovery (t+j) *Exportability index (1)			-0.009			-0.015	
			(0.009)			(0.009)	
Oil discovery (t+j) *Exportability index (2)				-0.006			-0.014
				(0.014)			(0.014)
Past giant discoveries (t-10)	0.002	0.006***	0.005***	0.005***	0.006***	0.005***	0.005**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Industry share (t-1)	-0.532***	-1.057***	-1.062***	-1.061***	-1.067***	-1.072***	-1.071***
	(0.044)	(0.073)	(0.073)	(0.073)	(0.071)	(0.072)	(0.072)
Observations	49481	56416	56416	56416	55908	55908	55908
R^2	0.065	0.049	0.049	0.049	0.049	0.049	0.049
Panel B: Wages							
Oil discovery (t+j)	0.004	-0.003			-0.023***		
	(0.006)	(0.006)			(0.006)		
Oil discovery (t+j) *Exportability index (1)			0.001			-0.023***	
			(0.007)			(0.008)	
Oil discovery (t+j) *Exportability index (2)				0.002			-0.023*
				(0.011)			(0.012)
Past giant discoveries (t-10)	0.002	0.005***	0.004***	0.004***	0.005***	0.004***	0.004***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Industry share (t-1)	-0.433***	-0.508***	-0.508***	-0.508***	-0.585***	-0.598***	-0.597***
	(0.034)	(0.034)	(0.034)	(0.034)	(0.038)	(0.038)	(0.038)
Observations	50577	57503	57503	57503	56259	56259	56259
R^2	0.080	0.072	0.073	0.073	0.074	0.073	0.073

Notes: All regressions control for the number of years with discoveries from t-10 to t-1, and country, industry and year fixed effects. Data sources: manufacturing employment is from UNIDO, INDSTAT2 database. Robust standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C-8: Oil discovery and the tradable industries using INDSTAT4 database from UNIDO at the 4-digit level of manufacturing

Outcome in year:	(1)	(2)	(3)	(4)
Panel A. Value added (t+5)				
Oil discovery	0.005			
	(0.016)			
Oil discovery (t+5)		-0.011		
		(0.015)		
Oil discovery (t+5) *Exportability index (1)			0.000	
			(0.021)	
Oil discovery (t+5) *Exportability index (2)				-0.032
				(0.034)
Past discoveries (t-10)	0.023**	0.016**	0.015*	0.016**
	(0.010)	(0.008)	(0.008)	(0.008)
Manufacturing share (t-1)	-0.185	-0.430**	-0.431**	-0.431**
	(0.226)	(0.209)	(0.210)	(0.209)
Observations	19061	30248	30248	30248
R^2	0.046	0.042	0.042	0.042
Panel B. Employment (t+5)				
Oil discovery (t+5)	0.003			
	(0.011)			
Oil discovery (t+5)		-0.018*		
		(0.010)		
Oil discovery (t+5) *Exportability index (1)			-0.006	
			(0.014)	
Oil discovery (t+5) *Exportability index (2)				-0.028
				(0.023)
Past discoveries (t-10)	0.001	0.004	0.002	0.003
	(0.007)	(0.005)	(0.005)	(0.005)
Manufacturing share (t-1)	0.197	0.006	0.005	0.005
	(0.196)	(0.172)	(0.172)	(0.172)
Observations	22512	34442	34442	34442
R^2	0.048	0.041	0.041	0.041
Panel B. Wages (t+10)				
Oil discovery (t+5)	-0.011			
	(0.012)			
Oil discovery (t+10)		-0.021*		
		(0.012)		

Oil discovery (t+10) *Exportability index (1)			-0.015	
			(0.018)	
Oil discovery (t+10) *Exportability index (2)				-0.034
				(0.025)
Past discoveries (t-10)	0.018***	0.011*	0.010	0.010
	(0.006)	(0.006)	(0.006)	(0.006)
Manufacturing share (t-1)	0.099	0.065	0.065	0.065
	(0.170)	(0.172)	(0.172)	(0.172)
Observations	30892	29568	29568	29568
R^2	0.061	0.064	0.064	0.064

Notes: All regressions control for the number of years with discoveries from t-10 to t-1, and country, industry and year fixed effects. Data sources: manufacturing employment is from UNIDO, INDSTAT4 database. Robust standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$