DEPARTMENT OF ECONOMICS
OxCarre (Oxford Centre for the Analysis of Resource Rich Economies)

Manor Road Building, Manor Road, Oxford OX1 3UQ
Tel: +44(0)1865 281281 Fax: +44(0)1865 281163
reception@economics.ox.ac.uk www.economics.ox.ac.uk

UNIVERSITY OF OXFORD

OxCarre Research Paper 192

Dutch Disease Resistance: Evidence from Indonesian Firms

James Cust
World Bank & OxCarre

Torfinn Harding
NHH Norwegian School of Economics

Pierre-Louis V'ezina
King's College London & Oxcarre

Direct tel: +44(0) 1865 281281 E-mail: celia.kingham@economics.ox.ac.uk

Dutch Disease Resistance: Evidence from Indonesian Firms*

James Cust
World Bank and OxCarre

Torfinn Harding
NHH Norwegian School of Economics

Pierre-Louis Vézina
King's College London and OxCarre

June 2, 2017

Abstract

Oil and gas extraction may lead to the Dutch disease, i.e. the crowding out of the manufacturing sector due to rising wages when labor is drawn to the expanding extraction and services sectors. In this paper we exploit the fact that oil and gas discoveries contain an element of chance as well as oil price fluctuations to capture random variation in oil and gas windfalls across Indonesia and identify their effects on manufacturing firms. We find that oil and gas windfalls cause wage growth but that the firm exit rate is unaffected. Firms' output and labor productivity increase along with wages suggesting where firms are able to respond to booming local demand, and raise productivity in response to upward wage pressures, they can overcome the crowding-out effects from resource windfalls.

Keywords: Dutch disease, firm level, Indonesia, manufacturing firms, oil and gas

JEL-codes: O13, O14, Q32

*Cust: jcust@worldbank.org, Harding: torfinn.harding@nhh.no, Vézina: pierre-louis.vezina@kcl.ac.uk. We'd like to thank Beata Javorcik, Peter Neary and Anthony Venables as well seminar participants at OxCarre, King's, and at the 2016 Royal Economic Society Meeting at Sussex for helpful comments as well as Wood Mackenzie for academic access to their PathFinder database. Support from the BP funded Oxford Centre for the Analysis of Resource Rich Economies (Oxcarre) and the Statoil chair in Economics at NHH is gratefully acknowledged. The findings, interpretations and conclusions do not necessarily reflect the views of the World Bank, its Executive Directors, or the governments they represent. All errors are our own.

1 Introduction

Whether natural resource wealth is a curse or blessing is still being debated, especially since the 2000s have seen an unprecedented commodity price boom and a series of discoveries in developing economies. The collapse in the oil price in 2014 and subsequent economic stress in countries like Brazil, Nigeria and Russia has, once more, put resource rich countries on the agenda of observers like the World Bank and the IMF. The worry is that a decade of booming resource sectors contributing to good aggregate economic performance have meanwhile weakened manufacturing sectors in these countries and hence reduced the potential for economic growth going forward, via the Dutch disease mechanism (Corden and Neary, 1982).

In this paper, we study the local effects of oil and gas booms on manufacturing firms in Indonesia. Our identification strategy is to compare manufacturing firms across districts (kabupatens) that differ in terms of yearly oil and gas windfalls. Detailed data on oil and gas exploration drilling allow us to calculate long-term district-specific oil and gas discovery rates. The idea is that discoveries, conditional on exploration drilling, are determined by geology and luck and represent exogenous variation in oil and gas exposure across districts. By combining the discovery rates with the world oil price, we generate plausibly exogenous variation in oil and gas windfalls across districts and years.

Indonesia provides an ideal setting for our study, as it is a relatively large emerging economy with a sizeable manufacturing sector. It is also resource-rich, with many regions producing oil and gas. Resource rents consistently account for more than 10% of GDP and 20% of exports over the last 20 years. This share is as high as that of all manufacturing exports which consisted mostly of textiles, plastics, rubbers, as well as machinery and electronics during the same period. To the best of our knowledge, this is the first paper providing evidence on the effects of oil and gas windfalls on manufacturing firms in an emerging economy. Note also that investigating Dutch disease dynamics within a country allows us to isolate the theoretical micro-foundations of Dutch disease from the general macroeconomic effects that might confound the relationship between resources and manufacturing at the cross-country level (van der Ploeg, 2011).

We find that a 10% increase in windfalls causes an overall 1.9% increase in wages in districts that got lucky with exploration, and no increase in product prices. We also find that windfalls raise labor productivity, as well as output and employment, and we find no effect on the probability of firm exit.

Given the literature on heterogenous firms, i.e. Melitz (2003) and a large related literature, we would expect firms with different productivity levels to perform differently faced with a cost shock like increased wages or demand shocks from a booming local economy. Allowing the effect of oil and gas windfalls to depend on the initial labor productivity of firms, we find that an oil and gas windfall makes low productivity firms significantly more likely to exit. However, windfalls also drive larger changes in wages, unit values, labor productivity and output. It seems that firms with relatively low labor productivity either die or grow in the wake of a windfall.

The use of intermediate inputs is found to increase due to windfalls, with a stronger effect for initially less productive firms. Regarding the introduction of new products or dropping of existing products, we find no effects of windfalls. There is some, but rather weak, support for windfalls reducing the share of output value that is exported.

These results are similar to Allcott and Keniston (2014), Cavalcanti et al. (2015) and Michaels (2011) in that wages (and then labor productivity) are found to increase in response to a boom. This would also be in line with the standard theory on the Dutch disease: windfalls increase wages to guide reallocations over to the non-tradable sector and the booming resource sector (Corden and Neary 1982). However, the standard theory prediction of a reallocation away from manufacturing (due to increased wages and a resulting appreciation of the real exchange rate) is not supported in our data. Instead, we find that manufacturing firms manage to grow in terms of output and employment. This may be due to local booms, e.g. increased demand by the resource sector and the non-traded sector in terms of, for example, public investments. Allcott and Keniston (2014) find the same in the US firm-level data, and the results of Cavalcanti et al. (2015) and Cust and Rusli (2014) of high growth in resource rich Brazilian municipalities and Indonesian districts, respectively, also go in the same direction.

Allcott and Keniston (2014) argue that whether manufacturing contracts during a local natural resource boom depends on three factors, i.e. whether local manufacturing wages rise, whether prices do not rise, and whether resource windfalls generate local productivity spillovers to manufacturing. Our results indicate that, in spite of no overall increase in unit values, the manufacturing sector in Indonesia has been resilient to the Dutch disease and remained resilient through the times of large resource windfalls. Our results suggest that the least productive firms were either driven out of business, increased the use of intermediate inputs or managed to serve growing local markets by increasing their output. Given that manufacturing may be special in terms of productivity spillovers (Matsuyama, 1992), these results are good news for the future growth prospects of Indonesia.

The first contribution of this paper lies in the identification strategy, which utilizes luck and geology in combination with the world price to identify the effect of resource booms. This stands in contrast to much of the rest of the literature, which has used either cross-sectional variation only, resource endowments or production over time that may be endogenous to factors other than geology, or prices in combination with weights across units that may be correlated with unobservable characteristics.[1] In terms of variation across districts, our strategy is similar to the strategy used by Cotet and Tsui (2013), who also exploited randomness in the success or failure of oil exploration to look at the effect of oil wealth on conflict across countries. It is also similar to Cavalcanti et al. (2015), who suggest that districts with drilling but no discovery are a valid counterfactual to extracting districts. Cassidy (2016) utilize information on geological basins to create an instrument for oil production across countries. Unlike these papers however, we observe and utilize precise information on the ratio of exploration drilling to success.

Several papers have utilized exogenous prices. For example, Bazzi and Blattman (2014) and Dube and Vargas (2013) study the effects of commodity price shocks on conflicts and Harding and Venables (2016) instrument natural resource exports with prices to study the effects on non-resource trade. A challenge with using prices as instruments, is that the weights

[1] Earlier empirical work on the Dutch disease includes Allcott and Keniston (2014), Ismail (2010), Bjørnland and Thorsrud (2016) and Kuralbayeva and Stefanski (2013) on manufacturing, Harding and Venables (2016) on non-resource trade and Cashin et al. (2004) and Chen and Rogoff (2003) on the real effective exchange rate. Brunnschweiler and Bulte (2008), van der Ploeg and Poelhekke (2010) and Cust and Harding (2014) highlight the issue of potentially endogenous resource measures in empirical work on the resource curse.

across treated units, like countries or districts, may be endogenous. Potential solutions are to use initial/early values of the weights, like Allcott and Keniston (2014), Bazzi and Blattman (2014) and Harding and Venables (2016), or instrumenting the weights, like Dube and Vargas (2013). We solve this challenge by using the variation in the long-run discovery rate across districts, which is determined by geology and luck rather than drilling efforts or other circumstances potentially correlated with the performance of the manufacturing sector.[2] The use of the world oil price helps us with mimicking variations in windfalls due to price changes and not production changes. What typically happens in our data is that production starts with a lag after a discovery is made and follows some extraction path depending on the size of the reservoir. Price booms, on the other hand, are quite different, creating large fluctuations in resource rents and following economic adjustment challenges. We follow firms over time, allowing us to analyze within-firm behavior as the windfalls accrue.[3] In this sense, we provide the first analysis that properly addresses the question: what happens to the survival and health of manufacturing firms located in a local booming resource economy?

The second contribution of this paper is that it studies manufacturing firms in a large emerging economy, for which detrimental growth effects may be most relevant and serious. Although the literature on the impacts of resource booms has recently turned away from cross-country income regressions à la Sachs and Warner (1995) to within-country investigations, very little attention has been given to the impact of resources on manufacturing firms. One recent exception is Allcott and Keniston (2014), who shows that manufacturing actually performs better, not worse, in resource-rich US counties. Meanwhile, Arezki et al. (2017) examine the comparative advantage effects of the US fracking boom on US manufacturing exports by sector classification. They find evidence supporting that relatively cheaper US gas has boosted US

[2] Recently, several papers have studied the effects of giant oil and gas discoveries on outcomes such as conflict (Lei and Michaels, 2014), macro economic adjustments (Arezki et al., 2016) and the real exchange rate (Harding et al., 2016). With our detailed drilling data we are able to construct long-run discovery rates, which is the closest one can get to observe the actual geology. Although seismic data on geology is available for many places, the uncertainty about the geology is surprisingly high: the average discovery rate *conditional on drilling* is only about 50% globally with large variation by location.

[3] The detailed manufacturing data allow us to control for unobservable time-invariant firm characteristics, such as firm location, with firm fixed effects and sector-year specific shocks, such as demand shocks, with sector-year fixed effects.

manufacturing in terms of exports, while on the intensive margin new energy-intensive manufacturing has been added as measured by large new investments.[4]

In terms of studies not focusing on manufacturing, James and Aadland (2011) showed that resource-dependent US counties exhibit more anemic economic growth, Cavalcanti et al. (2015) showed that oil discoveries significantly increase per capita GDP and urbanization across Brazilian municipalities, and Aragon and Rud (2013) found positive effects of a large gold mine on real income in Peru. Haas and Poelhekke (2016) showed that firms in eight resource-rich emerging economies report more constraints to doing business if they are located within 20km of active mines and that these constraints include access to educated workers and finance. Cust and Poelhekke (2015) provide an overview of the literature on within-country effects of natural resources.[5]

The paper proceeds as follows. In section 2 we describe the empirical strategy, our data and the setting of oil and gas production in Indonesia. In section 3 we present our results and in section 4 we conclude.

2 Data and empirical strategy

2.1 Empirical strategy

Oil and gas extraction may take place where institutions and infrastructure are best, and thus where manufacturing is also favored. To identify the effect of windfalls on manufacturing firms, we need exogenous variation in the location and timing of windfalls. Our strategy is to proxy oil and gas windfalls with the interaction of luck in oil and gas discovery in the district with yearly variation in oil prices. The number of wells drilled in a district may be determined

[4] While examinations of the Dutch disease using firm-level data are still scarce, Smith (2014) examined the impact of the oil price boom in the 1970s and the subsequent bust on manufacturing in oil-dependent countries. He showed that manufacturing exports, value added, wages, and employment actually increased during the boom, and that these effects decreased during the bust, albeit gradually. Harding and Venables (2016) studied manufacturing trade in a panel of countries and found that increased resource exports decreased exports of manufacturing goods.

[5] Other studies include Brollo et al. (2013), Caselli and Michaels (2013) and Borge et al. (2015) who use variation across municipalities to study the response of local politicians to resource windfalls. The two former find support in favor of the political resource curse in Brazilian municipalities, while the latter finds that higher local government revenue from hydropower reduces the efficiency in production of public goods across Norway.

by district-specific factors such as infrastructure and institutions, consistent with the finding of Cust and Harding (2014) that the amount of exploration across countries is an outcome of institutional quality. The discovery rate, i.e. the share of non-dry wells, is in contrast not found to vary with institutional quality across countries. We assume the same is true across districts in Indonesia. Instead, the discovery rate is likely to be determined by geology and luck.[6] Yearly variation in the oil price, which is set on the world market, can thus be combined with variation in luck across districts to generate exogenous variation in the location and timing of windfalls.[7]

We estimate the effect of oil and gas windfalls on firm-level outcomes across districts and years by the following regression:

$$Y_{it} = \alpha_i + \delta_{jt} + \beta L_i \times P_t + u_{it} \tag{1}$$

where L_i is luck, i.e. the number of non-dry wells over total wells drilled in the district of firm i, P_t is the oil price in year t in 2010 USD, α_i and δ_{jt} are firm and industry-year fixed effects. The former helps controlling for firm-specific time-invariant unobservables, such as location and brand name, whereas the latter helps controlling for time-varying shocks hitting specific sectors, such as global demand shocks. The unit of observation is the firm-year and we cluster standard errors two ways; on firms to take into account potential serial correlation and on district to adjust for any Moulton bias, as the treatment is observed at a more aggregate level than the outcome.

Note that we drop all districts that never explored for oil and gas. Our treatment intensity is captured by variation in luck in discovery across districts and in yearly variation in the oil price. This is similar to the identification strategy of Cavalcanti et al. (2015) who suggest that Brazilian districts with exploration but no discovery are a valid counterfactual to estimate the effect of discoveries. We improve on this approach by using the ratio of exploration success

[6]We define dry wells (versus those recorded as a discovery) using the industry standard definition. A dry well or dry hole in our data is denoted as such where evaluated to contain insufficient oil for commercial production. Wood Mackenzie analysis supplements the raw well data to include post-drilling well evaluation, allowing for a more accurate picture of the eventual result and assessment of the well, and not just the recorded result at the time of drilling.

[7]Cotet and Tsui (2013) also exploit randomness in success of oil exploration to look at effect of oil wealth on conflict. They find that oil discoveries do not increase the likelihood of violent challenges to the state

to drilling per district instead of a dummy and, most importantly, by using the oil price as time-variation rather than simply a dummy that remains one for all years post discovery.

We run parsimonious models with no control variables. The reason for this choice is that, with proper random variation, the role of the controls would be just to increase the precision of the estimates. However, including controls that are themselves potentially affected by the treatment makes the interpretation more difficult.

2.2 Data

Well exploration and production data are provided by the PathFinder database owned by Wood Mackenzie (2011). In Indonesia, it includes more than 1200 individual wells in over 40 districts (out of a total of 280 districts, known as kabupatens). Data on the oil price is from the BP Statistical Review of World Energy 2016.

Table 1: ”Two-digit industries, ISIC rev. 3”

isic_2d	isic_2d_name	N
15	Manu. of food products and beverages	7617
16	Manu. of tobacco products	1544
17	Manu. of textiles	3646
18	Manu. of wearing apparel; dressing and dyeing of fur	3112
19	Tanning and dressing of leather; Manu. of luggage, handbags, saddlery, harness and footwear	922
20	Manu. of wood and of products of wood and cork, except furn.; articles of straw and plaiting mat.	2186
21	Manu. of paper and paper products	709
22	Publishing, printing and reproduction of recorded media	990
23	Manu. of coke, refined petroleum products and nuclear fuel	232
24	Manu. of chemicals and chemical products	1384
25	Manu. of rubber and plastics products	1869
26	Manu. of other non-metallic mineral products	2579
27	Manu. of basic metals	406
28	Manu. of fabricated metal products, except machinery and equipment	1218
29	Manu. of machinery and equipment n.e.c.	650
30	Manu. of office, accounting and computing machinery	266
31	Manu. of electrical machinery and apparatus n.e.c.	427
32	Manu. of radio, television and communication equipment and apparatus	380
33	Manu. of medical, precision and optical instruments, watches and clocks	240
34	Manu. of motor vehicles, trailers and semi-trailers	425
35	Manu. of other transport equipment	453
36	Manu. of furniture; manufacturing n.e.c.	3122
37	Recycling	86
	Total	34463

The data on firms is from the Indonesian Manufacturing Census for the years 1990-2008. It covers all plants with more than 20 employees, i.e. more than 30,000 plants during 1990-2008.

This data provides us with information about wages, exit rates, employment, productivity, and output prices which we can compute using core products' unit values for which we have data from 1998 onwards. The distribution of sector of activity is given in Table 1. We look at wages, exit rates, and prices using core products' unit values.

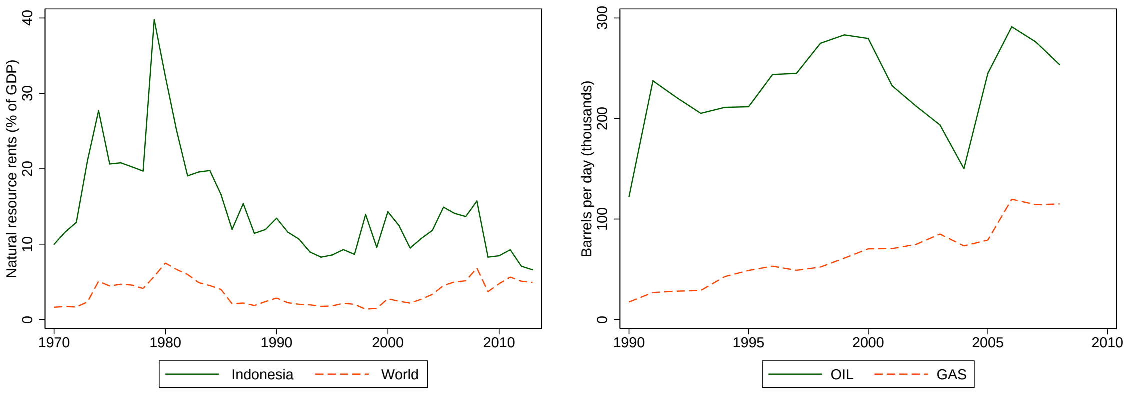
We follow Amiti and Davis (2012) and use the log of the average firm-level wage, defined as the total wage bill divided by the number of workers. We define the exit rate for each period as the share of firms we no longer observe in the subsequent period. Employment is simply the number of employees, which we can categorize as white or blue collar, labeled as production/non production workers in the data. We choose a simple ratio of output per employee as our measure of labor productivity. To proxy for output prices we use the unit values (value/volume) of the firm's core product, defined as the one with maximum value.

2.3 The setting: Indonesia

Indonesia first discovered oil in 1885 in North Sumatra. PWC (2014) suggests that in 2014 it accounted for 1.1% of world oil production. The country's main oil-producing provinces are Sumatra, the Java Sea, East Kalimantan, and Natuna. The same report estimates that Indonesia produced 2.1% of the world natural gas in 2012, making it the 4th largest natural gas producer. The main gas provinces are South Sumatra, Arun, East Kalimantan, and Natuna. McKinsey Global Institute (2014) says Indonesia has 22 billion barrels of conventional oil and gas reserves, of which 4 billion are recoverable. That is the equivalent of about 10 years of oil production and 50 years of gas. Nonetheless, Indonesia has been a net importer of oil since 2004.

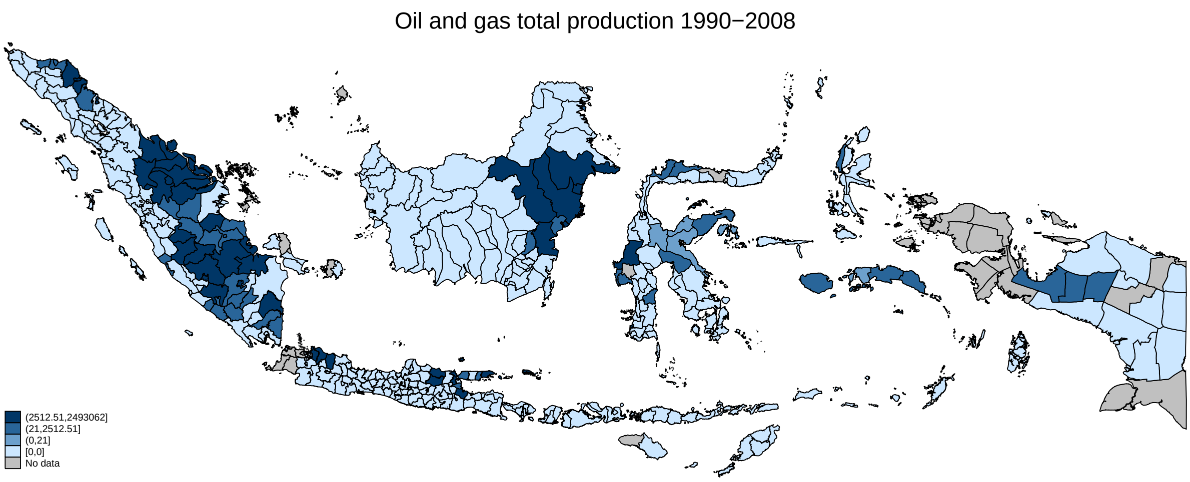
Indonesia is considered a resource-rich economy (IMF 2012), and the left hand panel in Figure 1 shows its high share of resource rents in GDP. It has experienced erratic oil production despite a gas boom and an oil price boom in 2000s (right hand panel, Figure 1). Figure 2 shows a map of oil and gas production by district in Indonesia. Oil production is spread out across the country and varies greatly in intensity, which creates the necessary support in our data. We observe manufacturing firms at different locations and hence exposed to different intensities of oil and gas windfall.

Figure 1: Resource rents and production of oil and gas



Resource rents in the left panel, and production of oil and gas in the right panel. Source: Resource rents from World Development Indicators, World Bank, and oil and gas production from the PathFinder database, Wood Mackenzie (2011).

Figure 2: Oil and gas production across districts in Indonesia



Note: Around 85% of districts have no oil or gas production in any period. 35% of production fields are offshore but can be linked to a closest district.

3 Effect of oil and gas windfalls

3.1 Within-country trends

To understand the trends within Indonesia we provide two sets of comparisons. First, we compare macro trends between districts with high exposure to oil with districts with low exposure to oil. Our preferred comparison is between lucky and unlucky districts, i.e. we exclude all districts that have not drilled for oil. Comparing unlucky with lucky mimics our identification strategy and provides a more convincing counterfactual than comparing municipalities in terms if their oil and gas production. Cust and Harding (2014) show that, across countries, oil exploration is endogenous with respect to the quality of institutions, whereas this is not true for the discovery rate. For these figures, we consider districts as *lucky* if their discovery rate is above 20% (in the regressions we instead use discovery rates as a continuous variable). For completeness, we compare also districts with oil and gas production vs. districts without such production. Figure 3 presents the trends for wages, exit rates and output.

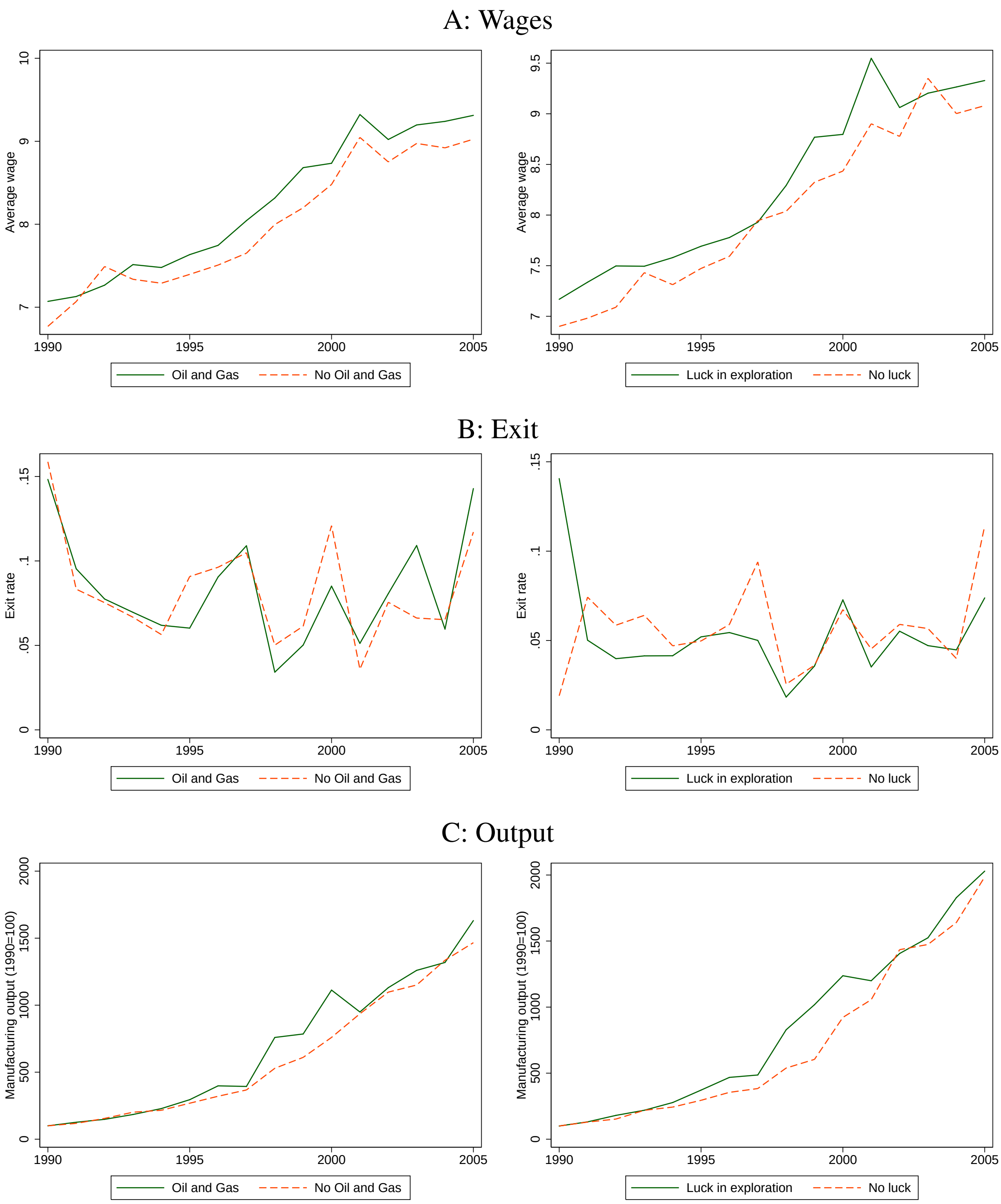
Panel A of Figure 3 suggests that oil and gas districts have been associated with higher wages on average across Indonesia, as predicted by the standard Dutch disease theory. The rate of wage growth, as seen from the slopes, also appears slightly higher when we compare lucky with unlucky.

In Panel B of Figure 3 we compare the average exit rates across the same comparison groups. We find no systematic differences in exit rates between lucky and unlucky districts or between districts with and without oil production. This is also what appears when we compare the number of firms across the type of districts (not shown to save space). None of the graphs on exit rates suggest that oil and gas production has forced manufacturing firms out of business, despite the Dutch disease symptom of higher wages.

In Panel C of Figure 3 we show that there is a distinguishable increase in total output in oil and gas producing and lucky districts during the period 1997-2000. This coincides with the growth in wages observed in Figure 3 as well as with a period of growth in the oil price. It thus suggests that manufacturing firms may have expanded when oil and gas windfalls increased.

These descriptive results are consistent with the theoretical literature on the Dutch disease in that they suggest that oil and gas windfalls are associated with higher wage growth, yet we do not observe a crowding out of the manufacturing sector. In the next section we explore the within-firm effect on wages and other outcomes with panel regressions.

Figure 3: Wages, exit and output



Note: Average wage is the mean across firms of our wage variable at the firm level, which is defined as (total wage sum)/(total employment). Exit rate is the share of firms that exit that year, i.e. for which this is the last year we observe them in the data. Manufacturing output is the sum of all firms' output. *Luck* in exploration means an average discovery rate above 20%. *No luck* means an average discovery rate below 20%. If there is no exploration, there is no discovery rate. *Oil and Gas* are districts that have oil or gas production at some point. *No Oil and Gas* have zero production over the whole period. Note that *No Oil and Gas* together with *Oil and Gas* include all districts in Indonesia. The "naive" way is to compare oil-and-gas districts to all the other ones (left hand side panels), and our preferred way is to compare the lucky ones with the unlucky ones among districts with drilling (right hand side panels).

3.2 Firm-level evidence

3.2.1 Wages and unit values

To estimate the effect of oil and gas windfalls on firms, we follow the model and identification strategy described in Section 2. Results are presented in Tables 2 and 3, which include reduced-form panel estimates focusing only on districts where there has been some oil and gas exploration. Note that we always include firm fixed effects and industry-year fixed effects, i.e. the estimates are based on within firm and within industry-year variation. In other words, they do not reflect reallocations across firms or changes to industries over time.

Table 2 focuses on wages and unit prices. Allcott and Keniston (2014) argued that the route to manufacturing contraction in the US went through a rise in local manufacturing wages but that prices should be exogenous or not affected by windfalls, as they are set in larger markets. In the upper panel, panel A, we estimate the average effect across all firms and find a positive and significant effect of oil and gas windfalls on wages. A 10% increase in windfalls leads to a 1.9% increase in wages. Columns (2) and (3) suggest that this rise in wages is driven by wages in production jobs, rather that white-collar jobs. Column (4) suggests that the firms' unit values of their core products are unaffected. So far, Dutch disease mechanics seem to be at play.[8]

In the lower panel, panel B, we allow for different effects of the windfalls depending on the firm's initial labor productivity. As emphasized by Melitz (2003) and the large related literature on heterogenous firms, firms' "productivity draw" determines their ability to overcome costs. Column (1)-(3) show the same qualitative result as before; the windfalls cause wages to increase, but the effect is significant only for blue collar workers. The effect is smaller in firms with higher initial labor productivity. When the competition for labor increased, there was presumably a greater need for raising the wages in firms with low labor productivity and, presumably, low wages. At the mean of labor productivity (8.58 in our sample), a 10% increase in windfalls leads to 2.9% higher wages among blue collar workers. At the 25th and 75th per-

[8] Average success rate is the average of the discovery rate, or luck as defined in our empirical strategy. Production and non-production wage are for white collar versus blue collar workers, labeled as production/non-production workers in the data. Unit value is (value/quantity) of the firm's core product, defined as the one with max(value).

Table 2: Wages and output unit values

A: Mean effect across all firms

	(1) Wage	(2) Wage production	(3) Wage non-production	(4) Unit value
Avg success rate x Oil price	0.190***	0.255***	0.116	0.067
	(0.043)	(0.050)	(0.231)	(0.093)
N	48194	48194	48194	46981
R-sq	0.80	0.91	0.80	0.85

B: Heterogenous effects, depending on initial labor productivity

	(1) Wage	(2) Wage production	(3) Wage non-production	(4) Unit value
Avg success rate x Oil price	1.253***	1.293***	0.433	2.051***
	(0.166)	(0.184)	(0.800)	(0.460)
× 1990 labor productivity	-0.111***	-0.117***	-0.038	-0.193***
	(0.018)	(0.021)	(0.090)	(0.051)
N	18550	18550	18550	18095
R-sq	0.81	0.92	0.80	0.85

Notes: Panel regressions with firm and industry-year fixed effects. Standard errors clustered by firm and kabupaten-year in parentheses. ***p<0.01, **p<0.05, *p<0.10. updated

centiles (7.61 and 9.45), the effect is 4.0% and 1.9%, respectively. Note that the sample in the lower panel of Table 2 is necessarily restricted to firms for which we observe labor productivity in the year 1990. In contrast, the upper panel includes all firms. We find it reassuring that the effects are qualitatively the same across the two samples. Note also that the effect in the upper panel is similar to the effect at the 75th percentile in the lower panel. It is reasonable that those firms who are able to stay in business inhabit the right hand side of the productivity distribution in the beginning of our period.

The result for unit values, presented in column (4), indicates that the less productive firms also increased their unit values more. For firms at the mean initial productivity, a 10% larger windfall increases the unit values by 4%, versus 2.3% and 5.8% at the 25th and 75th percentiles of productivity. Note that there is no effect on average, but the effect for low-productivity firms is large and significant.

3.2.2 Margins at which firms adjust

Table 3 looks at ten more outcomes at the firm level. Panel 1A and 2A present estimates of the mean effect across all firms, while Panel 1B and 2B again present estimates where we allow the effect to vary depending on the initial level of labor productivity.

Column (1)-(4) in panel 1A show no effect on exit rates, entry rates and the probability of product introduction or product drop. This suggests that there is no crowding out of the manufacturing sector due to oil and gas windfalls, in contrast with the standard Dutch disease theory and with the symptoms observed in the previous regression. Instead, we observe an increase in size, both in terms of output and employment (column (5)-(6), panel 1A). The increase in output is larger than in employment, resulting in an increase in labor productivity (column (1), panel 2A). We also find some weak evidence that the share of output exported falls, in line with an expanding local market due to windfalls (column (2), panel 2A). Column (4) in panel 2A suggests that an increase in purchased intermediate inputs is one channel through which labor productivity might increase.

Turning to the heterogenous effects in panel 1B of Table 3, we see that the aggregate masks considerable adjustments induced by the windfalls. Low productivity firms are more likely to exit, e.g., a firm at the 25th percentile has a 7% likelihood of exit due to an increase in oil and gas windfalls of 10% (column (1), panel 1B).[9] In terms of entry, product drop and introduction of new products, there are still no effects (column (2)-(4), panel 1B). For firm size in terms of output, the effect holds up: firms at the 25th percentile in terms of initial labor productivity, grow by 4.1 % when windfalls increase by 10%. Firms at the 75th percentile, grow by 1.3%. It seems that 'grow or die' is an appropriate description of the fate of low-productivity firms when the windfalls pour in. In this smaller sample, the growth does, however, seem to be of the jobless type, as we do not find an effect on employment.

Panel 2B of Table 3 reveals plenty of adjustments. As suspected from the growth in output but not employment, there is a significant effect on labor productivity, with a 10% increase

[9]Note that we always have the same firms in the sample, and some of these enter or exit during our sample period. We define exit as a dummy equal to 1 if it is the firm's last year, and entry if it is the firm's first year.

Table 3: Margins of adjustment

Panel 1: Exit and entry, product mix and size

A: Mean effect across all firms

	(1) Exit	(2) Entry	(3) Product drop	(4) Product intro	(5) Output	(6) Empl
Avg success rate x Oil price	-0.018	-0.006	0.018	-0.001	0.156***	0.073***
	(0.032)	(0.004)	(0.028)	(0.029)	(0.057)	(0.025)
N	48194	48194	48194	48194	48193	48194
R-sq	0.33	0.28	0.54	0.55	0.94	0.96

B: Heterogenous effects, depending on initial labor productivity

	(1) Exit	(2) Entry	(3) Product drop	(4) Product intro	(5) Output	(6) Empl
Avg success rate x Oil price	0.144***	0.006	0.018	-0.090	1.599***	0.022
	(0.056)	(0.010)	(0.085)	(0.087)	(0.246)	(0.087)
× 1990 labor productivity	-0.018***	-0.000	-0.002	0.009	-0.156***	-0.001
	(0.005)	(0.001)	(0.010)	(0.010)	(0.027)	(0.010)
N	18550	18550	18550	18550	18550	18550
R-sq	0.34	0.26	0.57	0.58	0.94	0.97

Panel 2: Productivity and trade

A: Mean effect across all firms

	(1) Labor Prod.	(2) % exported	(3) Share imported inputs	(4) Intermediate inputs
Avg success rate x Oil price	0.186***	-3.447*	0.012	0.123**
	(0.063)	(1.820)	(0.008)	(0.062)
N	48193	48194	47876	48192
R-sq	0.81	0.69	0.87	0.92

B: Heterogenous effects, depending on initial labor productivity

	(1) Labor Prod.	(2) % exported	(3) Share imported inputs	(4) Intermediate inputs
Avg success rate x Oil price	1.418***	-4.268	0.095**	1.567***
	(0.271)	(5.111)	(0.047)	(0.283)
× 1990 labor productivity	-0.127***	0.502	-0.011**	-0.157***
	(0.029)	(0.596)	(0.005)	(0.032)
N	18550	18550	18454	18550
R-sq	0.81	0.69	0.86	0.93

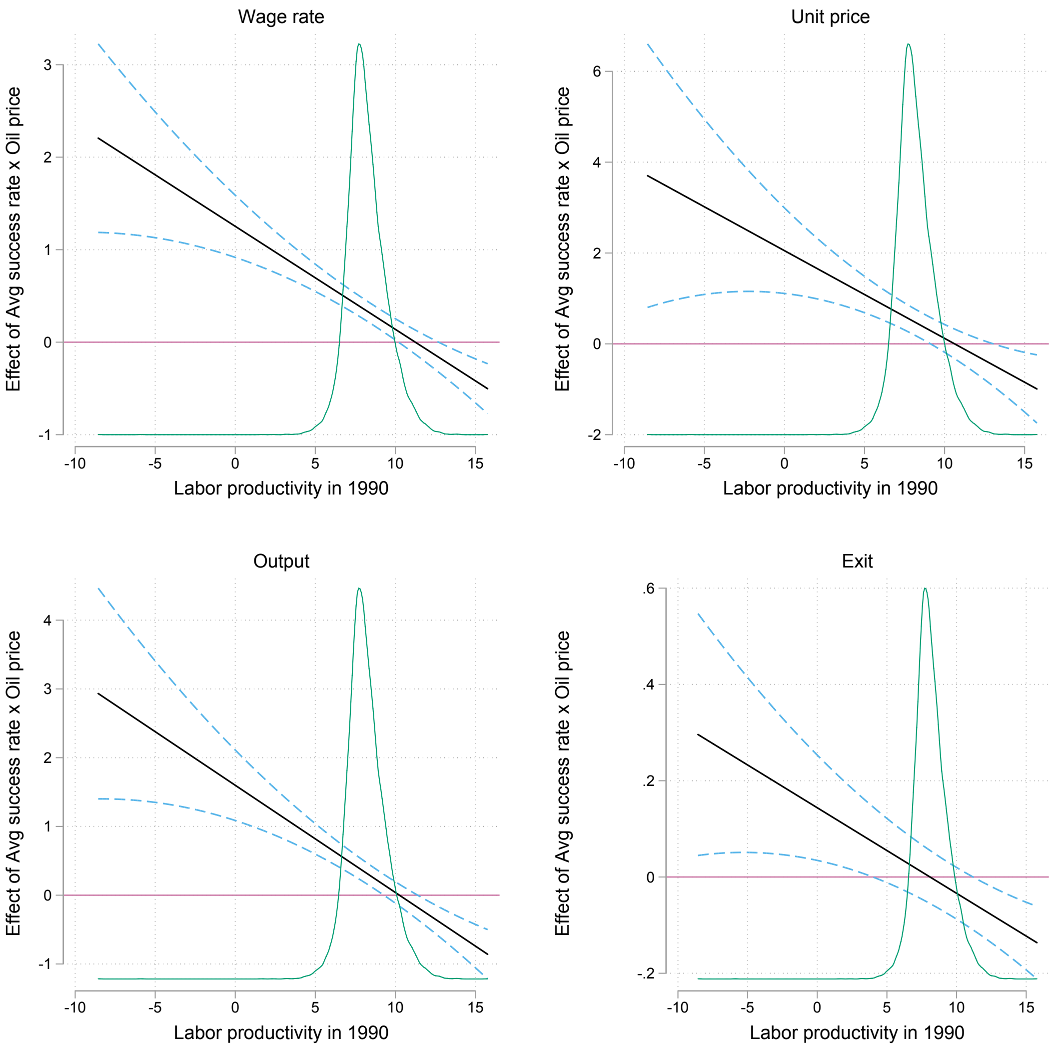
Notes: Panel regressions with firm and industry-year fixed effects. Standard errors clustered by firm and kabupaten-year in parentheses. ***p<0.01, **p<0.05, *p<0.10. updated in windfalls leading to an increase of 4.5%, 3.3% and 2.2% at the 25th percentile, mean and 75% percentile of initial labor productivity, respectively. Increased use of both imported intermediate inputs and intermediate inputs in general may be a channel through which the labor productivity increased (column (3)-(4), panel 2B). This channel is consistent with Amiti and Konings (2007), who found that reduction in tariffs and hence cheaper imported inputs increased productivity in Indonesian firms. In our setting, intermediate inputs may have become relatively cheaper compared to labor, which would increase the use of such inputs. Here, we do not find a significant effect on the export share.

3.3 Summing up the empirical evidence

In sections 3.2.1-3.2.2 we document important heterogeneity across firms in the adjustments to oil and gas windfalls. Figure 4 illustrates for four outcomes how the estimated effects of windfalls vary across the distribution of initial labor productivity of firms. For most of the firms, windfalls have led to a significant increase in wages, unit values and output. Only very productive firms could keep operating without much changes in these outcomes. For the likelihood of exit, on the other hand, a much smaller part of the distribution saw a significant effect. These results are consistent with firm expansions due to the windfalls, but with some firms going out of business.

The estimates in section 3.2.1-3.2.2 are based on regressions with firm and sector-year fixed effects, and do therefore not reflect reallocations across firms or sector-specific time shocks. To get a sense of the effects across different sectors, we plot in the left hand panel of Figure 5 the coefficients on the windfall measure in sector-specific regressions with firm and year fixed effects included. On the horizontal axis we measure the coefficients when we use wages as the dependent variable, and on the vertical axis the coefficients when we use the exit probability as the dependent variable. Most of the sectors see a zero or positive effect of windfalls on wages. For the exit probability, sectors making products such as like leather products, furniture and wood experience increased exit probabilities, whereas most of the others experience zero or negative effects. Zooming out to look for a correlation between the effect of wages and the

Figure 4: Heterogenous effects



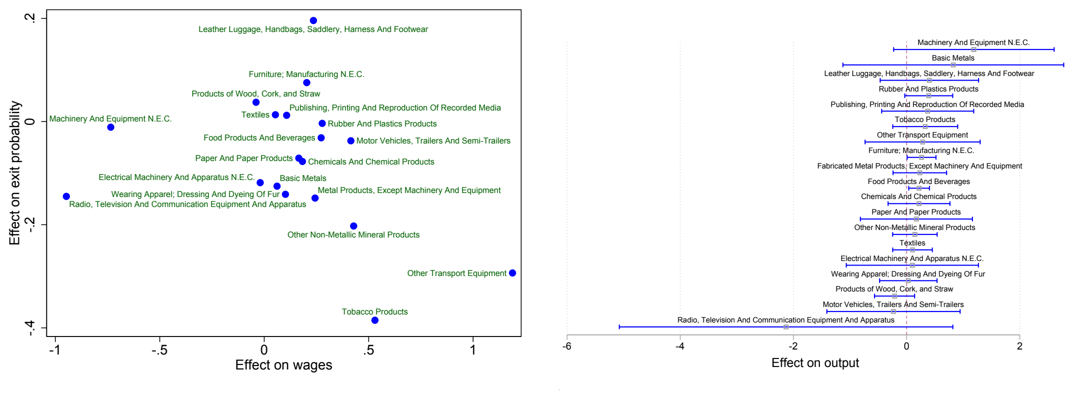
Note: Based on regression in Tables 2-3. The solid dark line plots the effect of windfalls on the outcome variable, written on top of the graph, the dashed lines are 95% confidence intervals, and the inverted u-shaped line gives the distribution of labor productivity across firms in 1990.

effect on exit rates in figure 5, there seem to be no obvious link between the two at the sector level.

The right hand panel of Figure 5 presents windfall coefficients when we instead use output as the dependent variable. Sectors like Machinery and Equipment (not elsewhere classified) and Basic Metals have shown strong positive responses, whereas sectors producing things like Motor Vehicles and Radio Equipment saw contractions.

The mixed picture we find, both across firms and sectors, may not be surprising. In Norway for example, a proportion of manufacturing firms were able to take advantage of the booming oil and gas sector by developing products to serve as inputs to this new industry (Bjørnland and Thorsrud, 2016). We do not see much evidence for such adaptation in our data- no single sector purchase or supplies more than 1% of its output from/to the oil and gas sector. However, similar to the Norway experience there may also be productivity spillovers from the oil and gas industry to the non-resource economy (Bjørnland and Thorsrud, 2016). For some sectors, however, higher labor costs may outweigh any such benefits and lead to contractions. This is supported by our finding that heterogeneity in firm exit appears to depend upon initial labor productivity, whereby higher performing firms are better able to adapt and survive.

Figure 5: Responses in wages, exit probability and output sector-by-sector



Note: The graphs show coefficients from our baseline regression run industry by industry.

4 Conclusions

We find evidence of Dutch disease symptoms in Indonesia such as rising wages in response to an exogenous resource boom. Firms face higher wages in 'lucky' booming oil and gas districts. Although unit values do not exhibit such an increase, we find no evidence to suggest firms are now more likely to exit in booming districts. Instead, firms adapt by raising their labor productivity. This study of Indonesia is thus in line with previous studies that highlight that the manufacturing sector is not crowded out by resource windfalls, but instead benefits from local booms. Our findings suggest that theoretical predictions of Dutch disease are not supported by within-country evidence at the firm level and therefore place some doubt on the micro-foundations for the Dutch disease hypothesis.

References

Allcott, H. and D. Keniston (2014, September). Dutch disease or agglomeration? the local economic effects of natural resource booms in modern america. Working Paper 20508, National Bureau of Economic Research.

Amiti, M. and D. R. Davis (2012). Trade, firms, and wages: Theory and evidence. *The Review of Economic Studies 79*(1), 1–36.

Amiti, M. and J. Konings (2007, December). Trade Liberalization, Intermediate Inputs, and Productivity: Evidence from Indonesia. *American Economic Review 97*(5), 1611–1638.

Aragon, F. M. and J. P. Rud (2013). Natural resources and local communities: Evidence from a peruvian gold mine. *American Economic Journal: Economic Policy 5*(2), 1–25.

Arezki, R., T. Fetzer, and F. Pisch (2017). On the comparative advantage of u.s. manufacturing: Evidence from the shale gas revolution. *Journal of International Economics 107*, 34 – 59.

Arezki, R., V. A. Ramey, and L. Sheng (2016). News shocks in open economies: Evidence from giant oil discoveries. *Quarterly Journal of Economics*.

Bazzi, S. and C. Blattman (2014). Economic shocks and conflict: evidence from commodity prices. *American Economic Journal: Macroeconomics 6*(4), 1–38.

Bjørnland, H. C. and L. A. Thorsrud (2016). Boom or gloom? examining the dutch disease in two-speed economies. *The Economic Journal 126*(598), 2219–2256.

Borge, L.-E., P. Parmer, and R. Torvik (2015). Local natural resource curse? *Journal of Public Economics 131*, 101 – 114.

Brollo, F., T. Nannicini, R. Perotti, and G. Tabellini (2013, August). The political resource curse. *American Economic Review 103*(5), 1759–96.

Brunnschweiler, C. N. and E. H. Bulte (2008). The resource curse revisited and revised: A tale of paradoxes and red herrings. *Journal of environmental economics and management 55*(3), 248–264.

Caselli, F. and G. Michaels (2013). Do oil windfalls improve living standards? evidence from brazil. *American Economic Journal: Applied Economics 5*(1), 208–38.

Cashin, P., L. F. Cespedes, and R. Sahay (2004). Commodity currencies and the real exchange rate. *Journal of Development Economics 75*(1), 239 – 268.

Cassidy, T. (2016). The long-run effects of oil wealth on development: Evidence from petroleum geology.

Cavalcanti, T., D. D. Mata, and F. Toscani (2015). Winning the oil lottery: The impact of natural resource extraction on growth. Technical report.

Chen, Y.-C. and K. Rogoff (2003). Commodity currencies. *Journal of International Economics 60*(1), 133 – 160.

Corden, W. M. and J. P. Neary (1982). Booming sector and de-industrialisation in a small open economy. *The economic journal*, 825–848.

Cotet, A. M. and K. K. Tsui (2013). Oil and conflict: what does the cross country evidence really show? *American Economic Journal: Macroeconomics 5*(1), 49–80.

Cust, J. and T. Harding (2014). Institutions and the Location of Oil Exploration. OxCarre Working Papers 127, Oxford Centre for the Analysis of Resource Rich Economies, University of Oxford.

Cust, J. and S. Poelhekke (2015). The local economic impacts of natural resource extraction. *Annual Review of Resource Economics* (0).

Cust, J. and R. D. Rusli (2014). The economic spillovers from resource extraction: a partial resource blessing at the subnational level? Economic Growth Centre Working Paper Series 1402, Nanyang Technological University, School of Humanities and Social Sciences, Economic Growth Centre.

Dube, O. and J. Vargas (2013). Commodity price shocks and civil conflict: Evidence from colombia. *Review of Economic Studies 80*, 1384–1421.

Haas, R. D. and S. Poelhekke (2016). Mining Matters; Natural Resource Extraction and Local Business Constraints. OxCarre Working Paper 175, Oxford Centre for the Analysis of Resource Rich Economies, University of Oxford.

Harding, T., R. R. Stefanski, and G. Toews (2016). Boom goes the price: Giant resource discoveries and real exchange rate appreciation. OxCarre Working Paper 174, Oxford Centre for the Analysis of Resource Rich Economies, University of Oxford.

Harding, T. and A. J. Venables (2016, June). The Implications of Natural Resource Exports for Nonresource Trade. *IMF Economic Review 64*(2), 268–302.

IMF (2012). Macroeconomic policy frameworks for resource-rich developing countries. Policy note, International Monetary Fund.

Ismail, K. (2010, April). The structural manifestation of the dutch disease'; the case of oil exporting countries. IMF Working Papers 10/103, International Monetary Fund.

James, A. and D. Aadland (2011, May). The curse of natural resources: An empirical investigation of U.S. counties. *Resource and Energy Economics 33*(2), 440–453.

Kuralbayeva, K. and R. Stefanski (2013). Windfalls, structural transformation and specialization. *Journal of International Economics 90*, 273–301.

Lei, Y.-H. and G. Michaels (2014). Do giant oilfield discoveries fuel internal armed conflicts? *Journal of Development Economics 110*(C), 139–157.

Matsuyama, K. (1992, December). Agricultural productivity, comparative advantage, and economic growth. *Journal of Economic Theory 58*(2), 317–334.

Melitz, M. J. (2003). The impact of trade on intra-industry reallocations and aggregate industry productivity. *Econometrica 71*(6), pp. 1695–1725.

Michaels, G. (2011). The long term consequences of resource-based specialisation*. *The Economic Journal 121*(551), 31–57.

PWC (2014). Oil and gas in indonesia. Investment and taxation guide - 6th edition.

Sachs, J. D. and A. M. Warner (1995, December). Natural Resource Abundance and Economic Growth. NBER Working Papers 5398, National Bureau of Economic Research, Inc.

Smith, B. (2014). Dutch Disease and the Oil and Boom and Bust. OxCarre Working Papers 133, Oxford Centre for the Analysis of Resource Rich Economies, University of Oxford.

van der Ploeg, F. (2011, June). Natural Resources: Curse or Blessing? *Journal of Economic Literature 49*(2), 366–420.

van der Ploeg, F. and S. Poelhekke (2010). The pungent smell of *red herrings*: Subsoil assets, rents, volatility and the resource curse. *Journal of Environmental Economics and Management 60*(1), 44–55.

Wood Mackenzie (2011). Pathfinder database, exploration wells dataset, accessed 10 10 2011. wood mackenzie pathfinder is a commercially-available database, updated quarterly, that contains worldwide exploration and production data for the petroleum industry. Technical report.

Table 4: Summary statistics

	N	Mean	SD	P25	P75	Min	Max
Wage	48194	9.09	0.99	8.52	9.72	0	16.38
Wage production	48194	13.19	1.76	11.95	14.37	0	21.93
Wage non-production	48194	10	5.03	9.31	13.38	0	21.03
Unit value	47063	3.83	2.9	1.71	5.63	0	20.47
Exit	48194	0.05	0.21	0	0	0	1
Entry	48194	0.01	0.08	0	0	0	1
Product drop	48194	0.42	0.49	0	1	0	1
Product intro	48194	0.4	0.49	0	1	0	1
Output	48193	15.66	2.33	13.83	17.38	8.08	24.5
Employment	48194	5.09	1.27	4.03	5.89	3.69	10.94
Labor Prod.	48193	10.18	1.49	9.15	11.07	1.47	17.55
% exported	48194	11.67	29.7	0	0	0	100
Share imported inputs	47899	0.12	0.28	0	0	0	1
Intermediate inputs	48192	15.08	2.44	13.2	16.87	0	24.47
Oil price (2010 USD)	48194	34.59	12.37	30.1	44.17	17.01	60.87
Avg success rate	48194	0.76	0.3	0.6	1	0	1
Avg success rate x Oil price	48194	2.65	1.07	2.05	3.41	0	4.11
Labor Prod. 1990	18863	8.58	1.33	7.61	9.45	2.35	13.79

Note: Wage, unit vale, output, employment, input and productivity variables are in inverse hyperbolic sines. The oil price is logged when interacted with the average success rate.