Oil price booms, Dutch disease and the crowding out of tradable sectors: New insight from bank lending behavior

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Abstract

The Dutch disease phenomenon is front and centre in explaining the poor economic performance of resource-rich economies. While it is well documented in the literature that resource discoveries or booms have adverse effects on manufacturing, little is known about the role of sectoral credit allocation in accentuating or mitigating this phenomenon. Using monthly sectoral loan data across 13 oil-rich countries over the period 1994-2017, we find the pattern of credit allocation to be consistent with the Dutch disease: oil price booms are associated with contraction (expansion) in manufacturing (services) sector share of credit. These findings are robust to a battery of robustness tests. Consequently, we argue that sectoral credit allocation is a channel through which productive resources are shifted toward the non-tradable sector at the expenses of the tradable sector. To the extent that financial systems in oil-rich economies efficiently intermediate resource windfalls, it could potentially countervail the Dutch disease syndrome.

Key Words: Dutch disease, sectoral credit, oil price boom, manufacturing sector, services sector

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1. Introduction

One common explanation for the poor economic performance of resource-rich economies is the so-called Dutch disease. It refers to the adverse effects of a resource boom or discovery on the manufacturing sector. The underlying proposition follows from the seminal idea of Corden and Neary (1982), that the sharp inflow of foreign currency from the resource boom leads to currency appreciation and wealth effects, which in turn make the domestic production and export of manufacturing sector less competitive[1]. Essentially, manufacturing is ''*crowded out*'' by the booming commodity sector, as often demonstrated by reduced investments in manufacturing sectors (Gylfason and Zoega, 2006).

While a sparse strand[2] of the literature explores the linkages between commodity markets and financial systems; so far, we know little about the extent to which bank credit policies or lending patterns accentuate or mitigate the cyclical effects of commodity prices on macroeconomic performance[3]. To what extent do banks countervail the Dutch disease through their credit screening and efficient intermediation function? How effective are the financial systems of resource-rich economies in serving as buffers towards smoothening economic performance over commodity cycles? Do sectoral lending patterns accentuate or mitigate the crowding-out of tradeable sectors? Do banks *see beyond* commodity price booms?

To our knowledge, there is no empirical evidence on bank lending behaviour or credit policy during commodity price booms; hence, the importance of our analysis is threefold. First, analysing sectoral credit flows during commodity booms could offer crucial insight into the potential role of credit markets in mitigating the Dutch disease. Specifically, we explore

[1] For instance, Ismail (2010) demonstrates that a 10% increase in the size of a commodity boom is associated with a 3.4% fall in manufacturing value added.
[2] For instance, a theme in this strand (e.g. Ploeg and Poelhekke, 2009; Beck, 2011; Beck and Poelhekke, 2017) suggests the existence of a natural resource curse in the financial sectors of resource-rich countries. A second theme (e.g. Kinda *et al*., 2016; Agarwal *et al*., 2017) attempts to link financial sector stability to negative commodity price shocks.
[3] See Beck (2016) for some discussions on the gaps in literature pertaining to financial markets and the resource curse.

the idea that banks' efficient intermediation business or capital allocation can potentially countervail the Dutch disease syndrome. Our underlying intuition is that banks' can *see beyond the boom*[4], hence behaving as if they were conducting countervailing monetary policy that smoothens economic performance over commodity cycles.

Secondly, credit allocation patterns across banking sectors in resource-rich countries could provide useful information on the strategic response of banks to commodity price movements. We argue that the strategic behaviour of lenders during commodity booms is an implicit indicator of financial sector development across resource-rich economies. Therefore, to the extent that bank lending behaviour is decoupled from commodity cycles, it represents an implicit indicator of financial system development and its potential resilience to adverse commodity shocks.

Thirdly, because this study employs decomposed sectoral bank credit data, it allows us to contribute to the literature on the sectoral concentration of bank assets, which is a major historical contributor to banking sector health (see Westernhagen *et al*., 2004). For instance, concentrated credit to booming sectors might potentially impose huge social costs and undesirable outcomes during negative price shocks. This speaks to the "*flight to quality*" arguments by Bernanke, *et al*. (1996) that borrowers who are likely to bear the adverse effects of exogenous shocks should, in principle, experience reduced credit access, relative to other firms/sectors.

In this paper, we attempt to answer the above questions using monthly sectoral loan data for a sample of 13 oil producing countries over the period 1994-2017. We apply a credit rationing model in which banks are faced with a range of projects across different sectors of the economy. To accomplish our empirical objective, we test the hypothesis that banks intermediate oil windfalls by allocating credit as if they were conducting countervailing

[4] This idea is based on the screening and credit rationing functions of banks. We discuss this idea in greater detail in our theoretical framework.

monetary policy to mitigate the Dutch disease. Specifically, we investigate the relationship between sectoral credit shares and oil price booms using an instrumental variables (IV) approach that addresses the potential endogeneity of oil price booms arising from positive oil price shocks due to events in sampled oil producing countries.

Exploiting exogenous variation in the magnitude and effects of oil price booms across sampled countries, we find that oil booms are associated with contraction (expansion) in manufacturing (services) sector share of banking sector credit. These findings are robust to a battery of robustness tests such as accounting for country-specific effects, addressing heterogeneity and endogeneity concerns, employing alternative measures of oil booms, amongst a range of other sensitivity tests. Given these findings, we reject the hypotheses that banks *see beyond the commodity boom* by allocating credit as if they were conducting countervailing monetary policy to countervail the Dutch disease through their credit screening and efficient intermediation function. The implications of our results are (i) sectoral credit allocation pattern across sampled economies represents a channel through which productive resources are shifted toward the non-tradable sector at the expenses of the tradable sector. (ii) monetary authorities across sampled countries have to take on the role of seeing beyond the boom as they cannot rely on the banks' efficient capital allocation business to carry out countervailing policies and (iii) sectoral credit flows provide useful insight on the sectoral productivity performance and wider macroeconomic performance of sampled oil-rich countries.

The remainder of the paper is organized as follows: Section 2 provides a theoretical framework to underpin our empirical model. In section 3, we discuss the empirical strategy and present our econometric model. Section 4 describes the data and descriptive statistics. In particular, we provide a detailed discussion on the potential measurement issues implicit in deriving a measure of oil price boom. Section 5 discusses the empirical results, along with robustness and sensitivity tests on the impact of oil booms on bank credit patterns. Section 6 concludes with some key policy implications and findings.

2. Analytical framework

2.1. Theoretical considerations

We seek to analyze the role of booming oil prices on bank credit allocation to key sectors of the economy. To the extent that booming oil prices are associated with relative contraction of credit to the tradeable sectors[5] of the economy, it suggests the presence of the Dutch disease syndrome. We follow the classic framework of Corden and Neary (1982) and Corden (1984) by assuming that each country in our sample has an economy that is characterized by a non-tradable sector N (e.g. services) and two other sectors including (i) the booming sector B (i.e. oil sector) and (ii) the lagging sector L (e.g. manufacturing sector). In this core model, we assume that output in each sector requires sector-specific capital and labour[6].

As shown by previous studies (e.g. Beck, 2011), a range of macroeconomic effects can arise because of the boom, but we focus on the most common *spending effect* whereby the oil windfall is spent into the economy (e.g. by the government or factor owners), raising the price of N relative to L since N is a normal good with a positive income elasticity. In short, L is weakened by the real appreciation in the relative prices in terms of N, drawing factor inputs out of L into N while also strongly stimulating demand for N relative to L. In the following sub-sections, we attempt to set out a theoretical model of banks' sectoral credit allocation, emphasizing the potential impact of uncertainty arising from exogenous sectoral shocks such as oil market shocks.

2.2.Bank credit policy and credit allocation

[5] We largely refer to manufacturing as the main tradeable sector.
[6] Labour is assumed to be mobile across the three sectors towards equalizing wages

We utilize a theoretical framework of bank credit allocation to motivate our empirical analysis. Our main task is to demonstrate how (and to what extent) credit policies are shaped or correlated with oil price booms across sampled countries. Following Rajan (1994), we set out by assuming that bank managers are rational but have concerns about short-run disruptions. Consider an economy with banks that have many potential borrowers across several sectors of the economy. Using a classic one-period model of bank credit allocation decision, we assume that each of the banks have only one type of asset: credit or loans (*C*) and two types of liabilities: capital (*K*) and deposits (*D*)[7], so we write the linear balance sheet constraint (ignoring other arguments such as required capital or asset ratio requirements, etc) as:

$$A = C = K + D \qquad [1]$$

The market for *C* and *D* are imperfectly competitive and are influenced by the market interest rate. Ignoring other model arguments for simplicity, we assume that banks maximize profits π as the margin between interest income on loans $r_L L$ and interest expense on deposits $r_D D$ less loan losses (δL):

$$\pi = (r_L - \delta)L - r_D D \qquad [2]$$

One critical attribute of the analysis above is that the size of π is a critical function of the efficiency or quality of the bank's credit allocation. We therefore posit that credit markets are different from standard markets, in that excess demand for credit is an ongoing phenomenon in the market such that many credit applications are not met. Hence, credit allocation is based on a rationing system[8]. Critically, this credit rationing assumption allows us to motivate our empirical credit allocation model as more of a supply schedule than a demand model.

2.2.1. Credit rationing and bank screening function

[7] Peek and Rosengren (1995).

[8] See Stiglitz and Weiss (1981) for a classic treatment of credit rationing by banks

To ration credit, banks must perform a screening function to distinguish between good and bad risks. Assuming that banks are faced with a range of projects across different sectors of the economy where for each project p in sector s there is a probability of returns R with different probability distribution across firm-sectors. However, banks cannot absolutely determine the riskiness of a project, so we can write the density function of the loan returns as

$$F = f(R, \theta) \quad [3]$$

where θ is a measure that is increasing in risk. Because the bank and borrowers across different sectors have differential information about project risks, there is scope for imperfect or asymmetrical information[9]. This creates uncertainty, the impact of which can be illustrated by considering a sectoral project with precisely two possible outcomes: a "good" outcome (O^G) and an inferior "bad" outcome (O^B) i.e. $(O^G > O^B)$. The likelihood of each outcome is P^G and P^B where $P^G + P^B = 1$ so that the expected value O^E

$$O^E = P^G O^G + P^B O^B \quad [4]$$

2.2.2. Classification of borrowers as a public good

Consider a one-period loan where the amount borrowed is B at an interest rate of r so that the expected repayment is $(1 + r)B$ with default occurring when $O < (1 + r)B$. It should be clear now that (i) expected repayment rises as the interest rate rises and (ii) falls as uncertainty δ rises. We therefore assume that banks prefer safer projects and higher loan rates while borrowers across different sectors prefer the opposite. This implies that expected repayment is a function of project riskiness so that banks classify borrowers/sectors based on their risk; hence it should be clear that $\theta'(\delta) > 0$ i.e. risk of default is an increasing function of uncertainty. Jaffee and Stiglitz (1990) suggest that this classification and screening function are front and center in the banking system allocation function in an economy. They

[9] Jaffee and Stiglitz (1990) assume that borrowers know the expected return and risks of their projects while banks only know the expected risk and return of the average project in the sector or economy

argue that the efficiency of credit allocation in the economy depends on the reliability of the borrower screening and classification function. The "public good" element of this function ensures that adverse market/sectoral conditions may be managed and mitigated in ways that the overall return to the society/economy is net positive. This is especially true in cases when an entire borrowing sector is hit by an (unpredictable) systematic adverse shock such as an oil price shock. In other words, there is a systematic sectoral component of uncertainty (Rajan, 1994), which explains Stiglitz's (1993; pp.23) views on the resource allocation role that banks play in an economy, arguing that *"if they fail, not only will the sector's profits be lower than they would otherwise have been, but the performance of the entire economic system may be impaired"*[10].

3. Identification strategy

Following from the theoretical idea on bank screening and allocation functions, we hypothesize as follows:

- H0. **Banks see beyond the commodity boom by allocating credit as if they were conducting countervailing monetary policy to intermediate oil windfalls and mitigate the Dutch disease**;
- HA. **Banks credit allocation mirrors commodity cycles and accentuates the Dutch disease by crowding out tradable sectors.**

The above hypotheses are ensued in the Dutch disease phenomenon and we assume that they could help deepen our understanding of how banks' lending behavior in resource rich economies contribute to mitigating the Dutch disease. In order to examine the relationship between oil price booms and sectoral credit allocation, we specify and estimate the baseline panel data regression as follows,

[10] See Rajan and Zingales (1998) and Galindo and Micco (2004) for some empirical evidence suggesting that the banking system's capital allocation towards sectors with the best economic viability can stimulate economic growth.

$$C_{kit} = \alpha_0 + \alpha_1 B_{it} + \boldsymbol{\gamma} \mathbf{z}'_{it} + \mu_i + \varepsilon_{it} \qquad [5]$$

where C_{kit} is the credit share of sector *k* in country *i* in period *t*, B_{it} is the boom variable for country *i* in time *t*, $\mathbf{z}'_{it}$ is a vector of banking sector and macroeconomic characteristics, μ_i represents country specific effects, and ε_{it} is the random error term. α_1 is our parameter of interest which measures the extent to which oil booms influence sectoral credit shares.

3.1.Instrumental Variables (IV) approach

The classic problem with the estimation of [5] is the potential endogeneity of the oil boom variable. Therefore, the identification of the parameters in [5] is a problem. Additionally, an underlying simultaneity problem arises from the fact that international oil prices are endogenously determined in a global supply-and-demand system. Although, we can observe market oil prices as equilibrium points of a reduced form relationship from transactions embedded within oil supply and demand functions, not all market covariates are observed. Moreover, other country-specific developments such as geopolitical events and market power in the global market power[11] could also influence world oil price movements (See Kilian, 2009).[12] While we can control for the fixed unobserved heterogeneity across sampled countries by purging these effects using a fixed effects model, other time-varying effects that may explain the variations in the impact of oil price booms across sampled countries might be embedded or conflated with random shocks in ε_{it}.

Given the discussions above on the oil demand and supply covariates; along with the other fixed and time-varying country specific factors implicit in μ_i and ε_{it}, respectively will

[11] For instance, consider the market power possessed by Saudi Arabia as a swing oil producer that could influence global oil prices by manipulating its supply levels.

[12] Additionally, each country in our data sample has its own economic, political, and institutional characteristics which might be correlated with other regressors. With panel data fixed-effects models, we can control for some of the country-specific effects, but other omitted variable and time varying influences are likely to be embedded in the random shock within the model which might bias parameter estimates.

be correlated with the boom variable B_{it} in the model [5]. Hence, the underlying identification problem implies that ordinary least squares (OLS) methods will not yield efficient or consistent estimates of the effects of the boom variables on bank lending behavior. Given the foregoing, we resort to an instrumental variables (IV) approach. Ideally, we need "good instruments" that possess the three key attributes of *relevance*, *validity* and *orthogonality* for the IV estimation to be efficient and consistent. To address this challenge, we can derive IV candidates for the oil price boom variable using exclusion restrictions on the demand and supply side of the oil market system. Specifically, we consider exogenous demand shifters that do not shift market supply and vice versa, or even exogenous factors that might influence both the demand and supply sides of the market[13].

3.1.1. Instrumental Variables (IV) candidates

Guided by theory and empirical evidence, we instrument for the oil boom variable using data from (i) total world oil rig count (ii) variable cost of oil production in the US (iii) average world temperature.[14] We take the world oil rig count data from Baker Hughes, Inc. database. We derive the variable cost of oil production using information on oil and gas employees, man-hours, wages and oil output from the U.S. Bureau of Labor Statistics and the U.S. Energy Information Administration (EIA). We take the average global temperature from the U.K. Met Office Hadley Centre observations datasets (Morice, *et al*., 2012). Notice that these instruments are either global or fall under regions outside sampled oil countries. This ensures exogeneity of the instruments. We then derive country-specific versions of the instruments by normalizing these global instruments with country-specific shares of total world oil reserves. This weight is appealing since it preserves the exogeneity of the resulting instruments given that oil endowment is naturally occurring phenomenon.

[13] See Manski (2003).
[14] See Lin (2008) for some discussions

4. Data and descriptive statistics

4.1.Data sample

To investigate the relationship between sectoral allocation of credit and commodity booms, we draw on a number of data sources: (i) several issues of central banks' statistical bulletins; (ii) the US Energy Information Administration's (EIA) database; (iii) BP Annual Statistical Bulletin; (iv) IMF International Financial Statistics (IFS); (v) the instruments for IV regressions are taken from the U.S. Bureau of Labor Statistics, *The Oil and Gas Journal*, Baker Hughes Inc. database, the U.K. Met Office, the World Bank Climate Change Knowledge Portal, and (vi) firm-level data on manufacturing enterprises are taken from the World Bank Enterprise Survey (WBES) to check firm-level dependence on external finance.

Our dataset comprises of monthly information on bank credit to manufacturing and services sectors across 13 oil producing countries over the period 1994-2017. Table 1 presents a background on our sampled countries using the latest available information (for 2016) on key economic indicators on income, oil contribution and financial development. Qatar, UAE and Bahrain have the highest per capita incomes, which are well in excess of the average income of $31,715 across the whole sample; whereas Indonesia, Nigeria and Côte d'Ivoire have the lowest income levels. The global oil production share indicates that our sampled countries account for around half of world oil production with Saudi Arabia (13.4%), Russia (12.2%) and UAE (4.4%) ranking as the top-three producers.

The average degree of resource dependence across our sample can be inferred from oil share of total goods export, which stood at 47% in 2016. Nigeria (91%), Kuwait (89%) and Azerbaijan (87%) appear to be the most reliant on oil, with the Latin American countries in our sample namely Mexico and Brazil being the least-dependent. Finally, we measure financial development using credit to the private sector as ratio of GDP. The average ratio for our sample is 55% with Nigeria (16%) being the least developed, in contrast to Malaysia (124%) and Kuwait (99%) at the top.

Table 1: **Income, oil contribution and financial development across countries, 2016.**

Country	**Per capita income (PPP, 2011=100)**	**Share of world oil production (%)**	**Oil share of total export (%)**	**Credit to private sector (% of GDP)**
Azerbaijan	15994.00	0.90	87.10	25.40
Bahrain	50719.12	0.02	50.35	73.72
Brazil	14023.69	2.80	6.34	62.18
Indonesia	10764.55	1.10	23.21	33.11
Kazakhstan	23419.91	1.80	60.74	30.77
Kuwait	35490.21	3.40	89.11	98.97
Malaysia	25660.46	0.80	16.09	123.97
Mexico	16831.12	2.70	6.07	26.80
Nigeria	5438.92	2.20	90.85	15.64
Qatar	118215.30	2.10	82.80	79.40
Russia	24026.00	12.20	63.00	54.72
Saudi Arabia	50458.17	13.40	78.40	57.98
UAE	67133.07	4.40	42.50	85.89

Source: BP annual statistical bulletin, World Bank Development Indicators (WDI)

4.2. Key variables and data sources

Our final dataset contains information on oil producing countries for which we could find data[15], yielding a data sample of 2206 observations. We deflate all monetary values to 2012 (2012 = 100) prices using monthly CPI data obtained from IMF IFS database. The deflated series are then converted to common international unit prices using the purchasing power parity (PPP) conversion factors. A brief description of the key variables are given in the following section.

4.2.1. Sectoral credit

[15] We try to include all oil producing countries, but in the end some countries have no monthly data on sectoral credit allocation. In some cases, some statistical bulletins do not offer the granular sectoral classifications that we employ in this study. For instance, these statistical bulletins only offer domestic credit allocation based on total “private” and “public” sector credit distribution. It is for these reasons that our dataset covers the 13 countries for which we could gather reliable data.

In order to analyze bank sectoral credit allocation during commodity booms, our dependent variable ought to reflect the changes in a sector's share of the banking systems total credit. Hence, we define and compute our dependent variable as:

$$C_{kit} = \frac{L_{kit}}{\sum_{j\neq k} L_{it}} \qquad [6]$$

where C_{kit} is the credit share of sector[16] k in country i in period t, L_{kit} is the total banking system[17] loans and advances to sector k across sampled countries and time periods, while $\sum_{j\neq k} L_{it}$ is the total loans and advances across all k sectors across country i during period t. The use of sectoral loan shares, as opposed to total loans across sectors ensures that we can capture or isolate the evolution of the relative importance of different sectors in the credit policy or allocation across sampled banking sectors. This approach is necessary, given that credit to the economy will likely move in certain directions during extreme economy events or shocks. For instance, credit is likely to expand across all sectors of the economy during economic booms and vice versa, albeit the rate of expansion or contraction may differ across sectors.

The compilation of a dataset suitable for our analysis required a major effort in terms of data collection as we rely on hand-collected sectoral breakdown of lending exposures. Specifically, we use sectoral credit composition data, which we collected from several hundreds of central bank monthly statistical bulletins across 13 oil-producers.

4.2.2. Defining and verifying the strength of oil price booms

[16] The sectors covered in our analysis are tradeable sector (i.e. manufacturing) and non-tradeable sector (i.e. services).

[17] Although we use banking sector-level flow of credit to industries, we considered bank level allocation. However, we note that due to the challenge that data on bank sectoral exposures are not directly available from commercial databases. Further, even when we considered a hand-collection based approach to deriving sectoral lending exposures at the bank level using publicly available financial statements, we observed that that the resulting database will be too limited in terms of the time series dimension (e.g. for many banks across sampled countries, we could only get data for around 5 years) due largely to missing observations attributable to high frequency of entry and exit in the banking sector, or mergers and acquisition. This limited timeframe is inadequate to study the evolution of commodity price booms. In addition, our detailed checks also demonstrate that the available sectoral loans data is limited to very large banks, which might not be representative of the overall banking system's business loan portfolio. Hence, we stick to the sectoral loan data obtained from statutory central bank credit registers.

Our main independent variable is oil price boom. While the definition of an economic boom is a straightforward matter, constructing its quantitative measure is a complicated matter. The complication arises from many considerations including (but not limited to) the potential endogeneity issues[18], as well as the quantitative precision of such boom measure (see Wu and Cavallo, 2012). Given these considerations, we set out to construct commodity boom measures as follows. Our starting point is that we conceptually define a boom as a period or episode of major and persistent deviations from an observed trend towards high states (Hamilton, 1989; Agnello and Schuknecht, 2011). To this end, we define an oil price boom using the conceptual idea that it refers to situations where actual market prices substantially exceed expected prices[19]. Consequently, we derive our oil boom measure as the percent deviations between actual and forecast oil price data in period *t*,

$$Boom_t = \begin{cases} 100 * \dfrac{(Actual_t - Forecast_t)}{Actual_t}, \text{during time } t \\ 0, \qquad \text{otherwise} \end{cases} \tag{7}$$

We use real oil spot prices as a proxy for actual prices, while the forecast prices are represented by real crude oil future contract data. Both price series are obtained from the EIA database[20]. The rationale for using futures prices (as a measure of commodity price forecasts) is that they embody market operators' best views and expectations about prices[21]. An added advantage of this approach is that these *market expectations* are accessible or observable by

[18] For instance, some oil price shocks are not entirely exogenous or unanticipated, such as in cases where swings in commodity prices embody endogenous changes such as shocks in major oil producing countries or slumps in the global macroeconomy. See appendix D for a graphical illustration of some of these events during our sample period.

[19] See Plante and Dhaliwal (2017)

[20] These oil price series are deflated using CPI data normalised to (2012=100).

[21] For instance, in a survey by Hamilton (2009) it is shown that, at the minimum, future oil prices embody rational expectations about future spot prices. Similarly, Wu and McCallum (2005) compare the forecasting performance of "futures-spot spread" with those of other forecasting models and they find that the futures-spot spread approach outperformed the other models, especially when the forecasting horizons are within few months, as is the case that we use monthly data in this study.

all oil producing countries. A second issue which we address is the size and relevance of the boom variable. It is plausible to imagine that an oil boom is likely to take heterogenous relevance or have varying levels of impact across oil-rich countries, depending on the degree of oil dependence across sampled countries. For this reason, following Deaton and Miller (1995) and Combes, *et al*. (2014), we normalize the boom measure in eqn. [7] using country-specific weights,

$$w_i = \frac{EV_b^{oil}}{EV_b^{Tot}} \qquad [8]$$

where w_i is a measure of oil dependence derived as the ratio of the value of oil exports EV_b^{oil} to total exports EV_b^{Tot} in base year b[22]. These country weights are sensible since the implication/size/relevance of an oil price boom for a country will depend on the degree of its economic dependence on oil. Furthermore, given that the resulting (fixed) weights are applied to the time-varying commodity boom variable for the different time periods, the resulting boom variable (i) retains the movements in global oil prices in eqn. [7] (ii) it embodies country-specific conditions via eqn. [8] and finally (iii) it mitigates the endogeneity concerns arising from unpredictability and country-induced supply side shocks.[23] Although, as noted by Musayev (2014), one limitation of this weighting scheme is that it might omit changes in the term of trade structure of sampled countries or even short-term dynamics arising from production shocks. For this reason, we explore alternative boom measures. See empirical results section.[24]

4.2.3. Strength of commodity price boom

We verify the robustness and reliability of our boom measure by verifying its strengths or correlation with conventional measures of commodity shocks from the literature. We

[22] Following the common practice in the literature, we take the sample mid-point as our base year: 2012.
[23] For instance, new oil discoveries or geopolitical events.
[24] See empirical results section.

hypothesize that our oil boom measure ought to embody positive oil price shocks. Following Kinda *et al*. (2016), we retrieve positive oil price shocks as follows. First, we regress real oil prices on their lags (up to three lags) and a quadratic time trend,

$$\ln P_{c,t} = \alpha_{c,0} + \alpha_{c,1}t + \alpha_{c,2}t^2 + \sum_{p}^{3} \theta_{c,p} \ln P_{c,t-p} + \varepsilon_{c,t} \tag{9}$$

The oil price shocks are then measured as the residuals of the regression above. The shock measure above also has an added advantage that, given that commodity prices can be I(1) or I(2), it makes the shock measure stationary and removes the predictable element from the stationary process (Kinda *et al.*, 2016). Secondly, since this study relates to price booms, we are only interested in the positive shocks, so we normalize the residuals by rescaling them between 0 and 1. Finally, in order to test the robustness of the boom measure, we regress the boom variable (from eqns. 7 and 8) on the positive oil shock variable (from eqn. 9) using robust standard errors. As shown in eqn. [10] below, the shock variable enters significantly at the 1% level of significance (t-statistics are reported in the parenthesis), indicating that the boom variable is positively associated with (or embodies/captures) positive oil price shocks. It is therefore powerful enough in capturing consistent upswings in oil prices

$$Boom_{it} = 0.78\ (5.68) + 3.17\ (4.96) * positive\_shock_{it} \tag{10}$$

$$R^2 = 0.46$$

4.3.Banking sector and other country-specific control variables

In addition to our main independent variable: commodity price booms, we control for an array of banking sector and macroeconomic characteristics such as total deposits, equity capital, interest rate, exchange rate, liquidity, size of the banking sector, institutional quality[25] and an OPEC dummy[26].

4.4.Descriptive statistics

Table 2 presents the descriptive statistics of the variables used in this study. The mean value of manufacturing share of loans is 12.5% with a standard deviation of 6.92%, compared to 41.7% and 4.7%, respectively for the services sector. Although left-skewed, the standard deviations for both variables suggest considerable cross-country variation in the level of sectoral bank credits. In particular, it is noteworthy to highlight that, on average, services sector share of credit is three times larger than manufacturing share of credit; bearing the hallmarks of the Dutch disease phenomenon. Unsurprisingly, agricultural share of bank credit is even much lower at 1.9% share of total credit during the period under review.

[25] See Appendix C for details on the construction of our institutional quality measure using principal component analysis (PCA).

[26] See Appendix A for detailed definitions and sources of the variables used in this study.

Table 2: Summary Statistics

Variable	Mean	Std. Dev.	Min	Max	# of countries	# of obs.
Banking sector-level data						
Agriculture share of credit (%)	1.91	1.84	0.001	8.73	13	2206
Manufacturing sector share of credit (%)	12.47	6.92	1.41	37.58	13	2206
Service sector share of credit (%)	41.68	4.74	26.35	49.30	13	2206
Oil price boom (%)	0.49	1.19	0.001	14.39	13	2206
Real interest rate (%)	10.26	7.01	3.30	73.78	13	2206
Total deposits (billion, ppp $)	18.80	66.20	0.03	548	13	2206
Total capital (billion, ppp $)	0.91	2.62	-0.02	20.40	13	2206
Real exchange rate (index, 2012=100)	111.31	39.36	62.52	395.12	13	2206
M2/Reserve	3.43	1.90	0.44	22.53	13	2206
Total assets (billion, ppp $)	6.49	13.10	0.04	83.70	13	2206
OPEC (Dummy=1, 0 otherwise)	0.44	0.50	0	1	13	2206
Institutional quality index	0.25	0.90	-1.68	2.01	13	2206
Instrumental variables						
Real unit labour cost of per barrel of oil in the US ($, 2012=100)	42.42	13.86	25.15	83.63		272
Average global temperature (degree Celsius)	0.52	0.17	0.10	1.11		272
OECD industrial index (2012=100)	97.47	8.83	78.28	110.00		272
Total world oil rigs	2315.34	1106.27	88.24	3900		272

5. Empirical results

5.1. Stationarity

We begin our econometric analysis with formal tests to examine stationarity (unit roots) for our panel data set. We conduct the first-generation Im, Pesaran, and Shin (2003) test (hereafter referred to as the IPS test), as well as the second-generation test of Pesaran (2007) which augments the IPS test by accounting for cross-sectional dependence across sampled countries (hereafter referred to as the CIPS test). Table B1 in the appendix presents results on these unit root tests. They indicate that the variables employed in this study are in general I(1) except exchange rate which is I(0). In particular, the results on both tests clearly indicate that the sectoral credit shares and the oil boom series are stationary variables.

5.2. Baseline results: oil price boom and sectoral credit flows

Next, we focus on the endogeneity of the boom measure using the Durbin-Wu-Hausman procedure where we test the corresponding orthogonality condition under the null hypothesis that it can be treated as exogenous. The test statistic, which is robust to heteroscedaticity or other violations of conditional homoscedasticity, is distributed as χ^2. This endogeneity test yields a test statistic of 11.96 with chi *p*-value = 0.000; rejecting the null that the boom variable is exogenous at conventional levels. This suggests that our specified model cannot be consistently estimated with OLS estimators under the assumption of orthogonality of the regressors.

Hence in our baseline results given in Table 3, we present both OLS and IV estimations for bank credit allocation to our sectors of interest. The first two columns pertain to the manufacturing sector, while the third and fourth columns are for service sector credit regressions. Our main analyses are based on the IV estimations, for which we instrument for the boom variable using global average monthly temperature, scaled by sampled countries' share of world oil reserves. We note that the appropriateness of the IV estimation depends on the use of “good instruments” that possess the key attributes of *relevance*, *validity* and *orthogonality*. Confirming these attributes requires a few considerations.

Table 3: Oil price boom and credit allocation: Baseline regressions

	Manufacturing loan share		Services loan share	
Variable	FE	FE-IV	FE	FE-IV
Boom	-0.0012*	-0.0107***	0.0011**	0.0076***
	[0.0007]	[0.0031]	[0.0005]	[0.0021]
Deposit	0.0102	0.0100***	-0.0023	-0.0014
	[0.0122]	[0.0038]	[0.0141]	[0.0033]
Capital	0.0026***	0.0031***	0.0048*	0.0043***
	[0.0029]	[0.0009]	[0.0025]	[0.0009]
Interest rate	0.1585***	0.1290***	-0.0973**	-0.0772***
	[0.039]	[0.0168]	[0.0454]	[0.0192]
Exchange rate	-0.0066**	-0.0095*	-0.0026	-0.0001
	[0.028]	[0.0053]	[0.0204]	[0.0044]
Liquidity	-0.0091**	-0.0108***	0.0044	0.0052***
	[0.0045]	[0.0013]	[0.0035]	[0.001]
Size	-0.0103*	-0.0100***	0.0035	0.0031***
	[0.0055]	[0.0012]	[0.0053]	[0.0011]
OPEC	0.0960***	0.0932***	-0.0512***	-0.0492***
	[0.0084]	[0.0055]	[0.0067]	[0.0032]
Institutions	0.0038	0.0040***	-0.0065	-0.0066***
	[0.0046]	[0.0008]	[0.0041]	[0.0007]
R-squared	0.61	0.54	0.49	0.42
Month dummies	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
Country dummies	Yes	Yes	Yes	Yes
Under id test: KP LM statistic		35.33		35.33
		[0.000]		[0.000]
Weak id test: KP LM statistic		37.94		37.94
		[19.93]		[19.93]
Over id test: Hansen J statistic		0.04		0.05
		[0.84]		[0.82]
Instrument		Weather		Weather
N	2206	2180	2206	2180

The dependent variables are the sector shares of total credit, defined as the ratio of manufacturing or services sector loans to total loans. Columns 2 and 4 report the OLS coefficients for both sectors. Columns 3 and 5 report IV estimates. The IV specifications use temperature, one and two lags. Kleibergen-Paap weak and underidentification LM and Wald tests are conducted under the null hypotheses that model is weakly identified and underidentified. For the weak id test, 10% maximal IV critical value in parentheses. For the under-id test, Chi p-values are reported in parentheses. Hansen test statistic of the over-identifying restrictions is asymptotically chi-square distributed under the null of instrument validity; p-values are reported in parentheses. Heteroskedasticity-robust standard errors reported in parenthesis are clustered for countries. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels respectively.

First, because we include fixed effects in the model, the instrument ought to have time and cross-sectional variations. Second, it must be correlated with $\Delta Boom_{it}$ and thirdly, it must be orthogonal to the firm-specific time varying elements remaining in the error process $\Delta\varepsilon_{it}$. The first consideration is verified, given that all instruments (global temperature, variable cost of oil production in the US and worldwide oil rig count) are time-varying variables. Additionally, cross-sectional variation in the instruments are ensured by the cross-country differences in share of world oil reserves (our instrument weights). For the second consideration, we resort to the strong statistical significance of the instruments in the first-stage IV regressions[27], while the third orthogonality condition can be tested in the context of an overidentified model using a Sargan (1958) or Hansen (1982) test of overidentifying restrictions.

Notice that the p-values of the Hansen *J*-statistics are 0.84 and 0.82 for the manufacturing and services sector regressions respectively, indicating that we fail to reject the null hypothesis that all instruments are uncorrelated with ε_{it}. Hence, the orthogonality conditions are satisfied, and the over-instrumentation problem is minimized in the IV regressions[28]. In particular, the Hansen *J* test results seem to be supported by a visual inspection of the IV estimates versus the OLS estimates in Table 3 which corroborates the importance of controlling for the endogeneity of the boom variable. We observe sizable differences between the OLS and IV estimates: the IV estimates for both sector regressions are numerically larger than the OLS estimates of the boom coefficient. This is expected since the OLS estimator does not account for correlation between country-specific events which may influence world oil markets and prices.

Turning now to the coefficient estimates on our main dependent variable, it is clear from the results presented in Table 3 that oil booms are associated with contraction (expansion) of credit shares to the manufacturing (service) sector. The IV estimates are

[27] See Table B2 in appendix

[28] The Kleibergen-Paap (2006) underidentification and weak identification LM test statistics also reject the null hypotheses that the IV models are underidentified or weakly identified

significant at 1% level, implying that banking sector credit allocation across sampled countries are pro-cyclical in a manner that is symptomatic of the Dutch disease: during booms, credit allocation is more favorable to the service sector but detrimental to the real sector (manufacturing). These findings are economically important as they indicate that banking sector credit flows/allocation are likely to amplify the Dutch disease syndrome. This is also consistent with the view that financial sectors across commodity rich economies might play contributory roles in the resource curse. This credit allocation pattern is potentially a channel/contributor to the falling investment in manufacturing during commodity booms.

We now consider the effects of the control variables in our baseline regressions. Controls include interest rate, exchange rate, size of the banking sector, liquidity, equity capital, customer deposits. We also control for institutional quality and OPEC membership. Their coefficients are largely consistent across estimators, and they appear to underpin the variation in results on the credit allocation across both sectors. For instance, notice that, apart from the coefficients on capital, the coefficients on the other controls indicate alternating signs that underscore the asymmetrical credit conditions across both sectors. Specifically, it appears that increased liquidity and larger banking sectors across sampled countries seem to favour the services sectors than manufacturing sectors.

As might be expected, countries with stronger institutions seem to allocate greater credit shares to manufacturing relative to services sector. This confirms the role of strong institutions in the allocation of resources within economic systems (Beck *et al.*, 2005; Hawkins, 2006). Interestingly, OPEC countries also seem to allocate more credit to manufacturing than the service sector. It is not immediately clear why this is the case, but the reason for this is outside the scope of this paper. The coefficient on exchange rate offers important insight on the currency appreciation channel of the Dutch disease phenomenon. An important element of the Dutch disease hypothesis is that currency appreciation hurts the real sector (manufacturing) since it raises their prices relative to other countries. Our real exchange rate data is the IMF's real effective exchange rate (REER): the real value of a currency against a weighted average of several foreign currencies. An increase in the REER indicates that exports have become more expensive and while imports become cheaper. The exchange rate coefficients for the service sector regressions are negative but not significant across the board. However, they are significant (and negative as well) the manufacturing sector regressions, a finding that is very much consistent with the impact of currency appreciation on manufacturing sectors. The results on capitalization is consistent with the view that both manufacturing and services sector loan shares are increasing in banking system capitalization. However, the bank deposits coefficients suggest that banks offer more to manufacturing than services sector when deposits increase. We check the robustness of these baseline results in Table 3 using a range of sensitivity tests which is now discussed in turns.

5.3.Robustness tests: quantile regression estimates

There might be concerns that our empirical results are seriously affected by undue outliers in the empirical distribution of our data. Hence, we use a quantile regression approach which is based on least absolute deviations rather than least squared residuals. This allows us to check the effects of oil booms at different points in the conditional distribution of sectoral credit shares. Specifically, a quantile regression is based on the parameter: q, the researcher's chosen probability level for isolating the proportion of the sample lying on or below the quantile regression line.

Table 4 presents the coefficient estimates of the quantile regressions across 0.1-0.9 quantiles. Notice that as the sectoral loan shares vary across quantiles, the estimated effect of the boom variable for the manufacturing sector is consistently negative and largely significant. In particular, as the manufacturing loan shares change across quantiles the estimate of the oil boom effect varies reasonably in terms of magnitude and degree of statistical significance. This is supported by the F-test statistic on the equality of the QR slope estimates which rejects the null that the slope estimates are equal at the 1% level. Therefore, the QR estimates are qualitatively analogous to the main results in Table 3.

We now turn to the QR estimates for the services sector credit shares which are presented in Table 5. In line with the main results, the QR estimates of the boom effect on the service sector loans are positive across the board, although some of the estimates lose statistical significance. Both sets of QR estimates therefore indicate that the relationship between oil price booms and sectoral loan shares across non-central regions or points of our data sample are consistent and similar to those obtained when using an approach based on the central tendency of probability distributions. Hence, we conclude that our results are robust to outlier problems.

Table 4: Robustness test: Quantile regression for manufacturing sector credit

	Quantile								
	0.1	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**
Boom	-0.0002	-0.0017***	-0.0021**	-0.0019*	-0.0015	-0.0019*	-0.0019*	-0.0028***	-0.0018
	[0.0004]	[0.006]	[0.009]	[0.008]	[0.0010]	[0.0011]	[0.0010]	[0.009]	[0.0012]
Deposit	-0.0014***	-0.0028***	-0.0045***	-0.0054***	-0.0039***	-0.0040***	-0.0026***	-0.0013	-0.0032**
	[0.0004]	[0.0005]	[0.0005]	[0.0006]	[0.0005]	[0.0006]	[0.0005]	[0.0012]	[0.0013]
Capital	0.0133***	0.0163***	0.0180***	0.0197***	0.0241***	0.0284***	0.0300***	0.0310***	0.0220***
	[0.0008]	[0.0012]	[0.0009]	[0.0014]	[0.0019]	[0.0016]	[0.0026]	[0.0054]	[0.0081]
Interest rate	0.1215***	0.1209***	0.1495***	0.1610***	0.1488***	0.1154***	0.0387**	0.0301	0.0020
	[0.0118]	[0.0146]	[0.0251]	[0.0185]	[0.0195]	[0.0219]	[0.0172]	[0.0238]	[0.0175]
Exchange rate	-0.0017	0.0022	-0.0076*	-0.0112	-0.0413***	-0.0507***	-0.0862***	-0.1083***	-0.0905***
	[0.0037]	[0.0045]	[0.0040]	[0.0077]	[0.0042]	[0.0055]	[0.0081]	[0.0110]	[0.0084]
Liquidity	-0.0087***	-0.0126***	-0.0146***	-0.0168***	-0.0221***	-0.0248***	-0.0154***	-0.0082**	0.0001
	[0.0019]	[0.0025]	[0.0016]	[0.0022]	[0.0027]	[0.0016]	[0.0026]	[0.0031]	[0.0037]
Size	-0.0019*	-0.0035***	-0.0042***	-0.0050***	-0.0091***	-0.0120***	-0.0097***	-0.0076	0.0056
	[0.0010]	[0.0012]	[0.0006]	[0.0010]	[0.0014]	[0.0017]	[0.0025]	[0.0066]	[0.0090]
OPEC	-0.0475***	-0.0466***	-0.0400***	-0.0376***	-0.0435***	-0.0471***	-0.0492***	-0.0439***	-0.0473***
	[0.0028]	[0.0025]	[0.0027]	[0.0037]	[0.0032]	[0.0033]	[0.0041]	[0.0036]	[0.0041]
Institutions	0.0001	-0.0010*	0.0015	0.0025*	0.0027**	0.0012	0.0012	-0.0042	-0.0057
	[0.0004]	[0.0006]	[0.0011]	[0.0014]	[0.0011]	[0.0012]	[0.0020]	[0.0034]	[0.0036]
Constant	0.0247	0.0251	0.0734***	0.0914***	0.2332***	0.2858***	0.3882***	0.4332***	0.3099***
	[0.0170]	[0.0225]	[0.0176]	[0.0329]	[0.0229]	[0.0245]	[0.0295]	[0.0612]	[0.0501]
N	2206	2206	2206	2206	2206	2206	2206	2206	2206
Equality of slope estimates							Test	F-statistic	p-value
0.1 vs [0.2…0.9]							0.1= [0.2…0.9]	3.32	0.0016

The dependent variable is the ratio of manufacturing sector loan to total loans. The results are based on quantile regression approach reported in columns 2-10. Consistent standard errors which are reported in the brackets are obtained using bootstrapping. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels respectively

Table 5: Robustness test: Quantile regression for services sector credit

	Quantile								
	0.1	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**
Boom	0.0008**	0.0005	0.0013	0.0006	0.0006	0.0006	0.0002	0.0011***	0.0001
	[0.0003]	[0.0005]	[0.0010]	[0.0006]	[0.0005]	[0.0005]	[0.0007]	[0.0003]	[0.0002]
Deposit	0.0030***	0.0006	-0.0005	0.0012*	0.0019***	0.0021***	0.0024***	0.0025***	0.0021***
	[0.0010]	[0.0013]	[0.0008]	[0.0007]	[0.0004]	[0.0003]	[0.0003]	[0.0003]	[0.0002]
Capital	-0.0187***	-0.0196***	-0.0185***	-0.0144***	-0.0131***	-0.0114***	-0.0099***	-0.0074***	-0.0051***
	[0.0016]	[0.0026]	[0.0022]	[0.0019]	[0.0010]	[0.0008]	[0.0012]	[0.0012]	[0.0006]
Interest rate	-0.4228***	-0.1468**	-0.0978***	-0.1098***	-0.1581***	-0.1788***	-0.2062***	-0.1928***	-0.1577***
	[0.0694]	[0.0650]	[0.0230]	[0.0275]	[0.0165]	[0.0133]	[0.0110]	[0.0114]	[0.0127]
Exchange rate	0.0639***	0.0659***	0.0566***	0.0392***	0.0209***	0.0150***	0.0098***	0.0058**	0.0068***
	[0.0069]	[0.0045]	[0.0043]	[0.0061]	[0.0031]	[0.0033]	[0.0034]	[0.0024]	[0.0018]
Liquidity	0.0131***	0.0108***	0.0086***	0.0114***	0.0138***	0.0141***	0.0141***	0.0140***	0.0125***
	[0.0040]	[0.0029]	[0.0021]	[0.0021]	[0.0014]	[0.0007]	[0.0013]	[0.0009]	[0.0004]
Size	-0.0002	0.0043	0.0071**	0.0040**	0.0044***	0.0036***	0.0025***	0.0005	-0.0012*
	[0.0021]	[0.0031]	[0.0025]	[0.0017]	[0.0009]	[0.006]	[0.0008]	[0.0010]	[0.0007]
OPEC	0.0213***	0.0202***	0.0203***	0.0242***	0.0214***	0.0200***	0.0223***	0.0237***	0.0234***
	[0.0043]	[0.0034]	[0.0033]	[0.0029]	[0.0026]	[0.0011]	[0.0022]	[0.0016]	[0.0009]
Institutions	-0.0043	0.0097**	0.0141***	0.0073***	0.0080***	0.0079***	0.0060***	0.0028***	0.0018***
	[0.0037]	[0.0047]	[0.0023]	[0.0017]	[0.0013]	[0.0007]	[0.0013]	[0.0006]	[0.0003]
Constant	0.2919***	0.2413***	0.2543***	0.3112***	0.3751***	0.4145***	0.4484***	0.4673***	0.4577***
	[0.0420]	[0.0306]	[0.0236]	[0.0245]	[0.0155]	[0.0148]	[0.0179]	[0.0135]	[0.0093]
N	2206	2206	2206	2206	2206	2206	2206	2206	2206
Equality of slope estimates							Test	F-statistic	p-value
0.1 vs [0.2…0.9]							0.1= [0.2…0.9]	2.23	0.0296

The dependent variable is the ratio of services sector loan to total loans. The results are based on quantile regression approach reported in columns 2-10. Consistent standard errors which are reported in the brackets are obtained using bootstrapping. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels respectively

5.4.Robustness tests: alternative measures of oil booms

Although we derive our boom variable from the underlying deviation of actual oil prices from forecast series, it is possible that this measure might incorrectly infer the magnitude of oil price booms, especially in instances where market expectations (upon which price forecasts are based) are inaccurate or misplaced. Therefore, we use an alternative oil boom variable which we constructed using the Hamilton's (1996) net oil price measure (NOP)[29]. Consider the log level of monthly oil prices as op_t so that the monthly changes in oil prices is given by $\Delta op_t = (op_t - op_{t-1})$; these changes can be decomposed into *increases only* (op_t^+) and *decreases only* (op_t^-), so that our boom measure pertains to the *increases only* measure

$$op_t^+ = \max(0, \Delta op_t) \qquad [11]$$

To construct the NOP variable that measures oil price increases, Hamilton then suggested to compare oil prices with where they had been over the previous year, rather than where it was the previous month, so that the NOP pertains to the maximum value of oil price during the preceding year, i.e. it is the increase from the previous year's monthly high price if it is positive, but zero otherwise:

$$nop_t = \max[0, op_t - \max(op_{t-1}, op_{t-2}, \dots, op_{t-12})] \qquad [12]$$

Using this measure, we then derive country-specific equivalents using the weights in eqn. [8]. Finally, our second country-adjusted boom measure can be specified as

$$Boom_{it}^2 = nop_t \times w_i \qquad [13]$$

A third, yet intuitive measure of oil boom is that based on break even prices (BEP). The external breakeven oil price is the oil price at which an oil-rich country's current account balance is zero. The alternative fiscal breakeven price (the oil price that is needed for an oil exporting country to balance its budget in time *t*), suffers from serious limitations, despite its

[29] Similar applications can be found in Borenstein et al. (1997); Gately and Huntington (2002); Griffin and Schulman (2005). See also Bjørnland (2009) and Wang, et al. (2013) for applications in financial market research.

appeal that many oil producers rely heavily on oil revenue to finance their fiscal spending. Setser and Frank (2017) highlight these limitations as including the reality that (i) budget revenues from oil are hardly reported transparently (ii) key government spending is sometimes kept off-budget and (iii) fiscal accounting or calculations vary across countries, making accurate comparisons impossible.

However, the external breakeven price is a more complete measure that can be consistently estimated and easily verified[30]. Intuitively, it also embodies the reality that an oil exporter's currency is likely to adjust to compensate for changes in fiscal or budget positions-weaker currencies stimulate the local currency oil export revenue values towards stabilizing government revenue. Hence, we derive a third oil boom measure from the magnitude by which actual oil prices exceed the external break-even oil prices. This boom variable is consistent with the reality that such market situations carry the potential for additional fiscal spending, as might be obtained with the alternative fiscal breakeven prices. The external breakeven price is calculated by subtracting a country's current account balance CA_{it} ($) from the value of its net oil exports revenue EV_b^{oil} ($) and dividing this measure by the volume of net oil exports (barrels):

$$BEP_{it} = \frac{EV_{it}^{oil} - CA_{it}}{Q_{it}^{oil}} \qquad [14]$$

As with the previous measures, we derive country-specific measures on the third boom using country weights,

$$Boom_{it}^{3} = [0, (op_t - BEP_{it}) * w_i] \qquad [15]$$

[30] See Setser and Frank (2017) for a very detailed discussion.

Table 6: Robustness test: Alternative boom measures.

	Manufacturing loan share		Services loan share	
	Hamilton	Break-even	Hamilton	Break-even
Boom	-0.1314***	-0.0514***	0.0935***	0.0363***
	[0.0370]	[0.0122]	[0.0255]	[0.0084]
Deposit	0.00370	0.0075**	0.0028	0.0004
	[0.00390]	[0.0034]	[0.0035]	[0.0033]
Capital	0.0020**	-0.0012	0.0051***	0.0073***
	[0.0008]	[0.0015]	[0.0009]	[0.0014]
Interest rate	0.1523***	0.1728***	-0.0943***	-0.1081***
	[0.0163]	[0.0195]	[0.0192]	[0.0209]
Exchange rate	-0.0161***	-0.0185***	0.0043	0.0062
	[0.0062]	[0.0062]	[0.005]	[0.0050]
Liquidity	-0.0123***	-0.0166***	0.0061***	0.0092***
	[0.0013]	[0.0016]	[0.001]	[0.0012]
Size	-0.0110***	-0.0106***	0.0039***	0.0035***
	[0.0014]	[0.0012]	[0.0012]	[0.0011]
OPEC	0.0902***	0.0937***	-0.0471***	-0.0495***
	[0.0057]	[0.0053]	[0.0033]	[0.0030]
Institutions	0.0042***	0.0041***	-0.0068***	-0.0067***
	[0.0008]	[0.0008]	[0.0007]	[0.0007]
(Centered) R-squared	0.56	0.58	0.42	0.45
Month dummies	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
Country dummies	Yes	Yes	Yes	Yes
Under id test: KP LM statistic	65.91	111.77	65.91	111.77
	[0.000]	[0.000]	[0.000]	[0.000]
Weak id test: KP LM statistic	33.25	88.94	33.25	88.94
	[19.93]	[19.93]	[19.93]	[19.93]
Over id test: Hansen J statistic	0.28	0.15	0.41	0.22
	[0.60]	[0.70]	[0.52]	[0.64]
Instrument	Weather	Weather	Weather	Weather
N	2180	2180	2180	2180

This table reports robustness tests of oil price boom and credit using an alternative boom measure based on Hamilton (1996). The dependent and other independent variables are analogous: manufacturing and service sector shares of total credit–defined as the ratio of manufacturing or services sector loans to total loans. Columns 2 and 4 report the OLS coefficients for both sectors. Columns 3 and 5 report IV estimates. Kleibergen-Paap weak and underidentification LM and Wald tests are conducted under the null hypotheses that model is weakly identified and underidentified. For the weak id test, 10% maximal IV critical value in parentheses. For the under-id test, Chi p-values are reported in parentheses. Hansen test statistic of the over-identifying restrictions is asymptotically chi-square distributed under the null of instrument validity; p-values are reported in parentheses. Heteroskedasticity-robust standard errors reported in parenthesis are clustered for countries. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels respectively.

The regression results pertaining to the two alternative boom measures are presented in Table 6. The model estimations indicate that credit contraction (expansion) to the manufacturing (services) sector are associated with booming oil prices. The sign on the coefficients are consistent across estimated models, corroborating our earlier findings. Therefore, we conclude that our findings are robust to alternative boom measures.

5.5.Robustness tests: additional checks

There might be some valid criticisms of our analyses so far: (i) using the manufacturing sector as the tradeable sector of oil producers might be inappropriate since the manufacturing sectors across these economies are weak, and therefore face greater credit constraints[31] (ii) as a result of (i) above, manufacturing firms hardly rely on external finance. To address these issues, we undertake two additional analyses as follows.

5.5.1. Alternative tradeable sector

First, we designate the agricultural sector as an alternative tradeable sector and use the loan shares of this sector as our alternative dependent variable in the tradeable sector regression. The regression results for this alternative tradable sector are presented in Table 7. Contrary to the previous sectoral loan share regressions, we use variable costs of oil production and number of oil rigs as instruments to identify the effects of oil booms on agricultural loan share. Intuitively, agricultural performance (and by extension its credit prospects) can be buffeted by weather-related shocks, such that the weather instrument is likely to be correlated with the unmeasured agricultural sector outlook embedded in the random error term of the model.[32] Hence, we use variable cost of oil production and rig counts to instrument for the boom variable. Our underlying finding that credit allocated to the tradeable sector contracts

[31] See Beck, *et al*. (2005) and Yuxiang and Chen (2011)
[32] In this case the orthogonality conditions will be violated.

during oil booms remains intact. Hence our findings are robust to alternative tradeable sector specifications/definitions.

Table 7: Robustness test: IV Alternative tradeable sector.

	FE-IV
Boom	-0.0072***
	[0.0020]
Deposit	0.0064***
	[0.0018]
Capital	-0.0019**
	[0.0008]
Interest rate	0.0650***
	[0.0156]
Exchange rate	-0.0021
	[0.0023]
Liquidity	0.0003
	[0.0007]
Size	-0.0024***
	[0.0007]
OPEC	0.0086***
	[0.0010]
Institutions	-0.0003
	[0.0003]
R-squared	0.40
Month dummies	Yes
Year dummies	Yes
Country dummies	Yes
Under id test: KP LM statistic	26.91
	[0.000]
Weak id test: KP LM statistic	12.49
	[19.93]
Over id test: Hansen J statistic	1.84
	[0.17]
Instrument	Oil rig & cost
N	2193

This table reports IV robustness tests of oil price boom and credit using an alternative tradeable sector- agricultural sector. The independent variables are analogous while the dependent variable is agricultural sector share of total credit: defined as the ratio of manufacturing or services sector loans to total loans. We use variable cost of oil production and lagged global oil rig counts. Kleibergen-Paap weak and underidentification LM and Wald tests are conducted under the null hypotheses that model is weakly identified and underidentified. For the weak id test, 10% maximal IV critical value in parentheses. For the under-id test, Chi p-values are reported in parentheses. Hansen test statistic of the over-identifying restrictions is asymptotically chi-square distributed under the null of instrument validity; *p*-values are reported in parentheses. Heteroskedasticity-robust standard errors reported in parenthesis are clustered for countries. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels respectively.

5.5.2. Firm-level analysis of external finance dependence

Secondly, we explore the potential criticism about the credit reliance of manufacturing sectors across sampled countries. If firms across these economies are less dependent on external finance/bank loans, then the implications of the loan pattern results in this study might be somewhat tempered. We therefore investigate the role of loan dependence across a panel of manufacturing firms in 8 of the 13 sampled countries. First, we collect firm-level data[33]on manufacturing enterprises from the World Bank Enterprise Survey (WBES)[34]. Following Rajan and Zingales (1998) and Cetorelli and Gambera (2001), we measure firm external finance dependence as,

$$Dep_{it} = \frac{Loan_{it}}{Cost_{it}} \qquad [16]$$

where $Loan_{it}$ is the total value of bank loan secured by firm *i* during period *t* while $Cost_{it}$ is the firm's cost of production. We present a range of statistical measures and indicators on this variable in Table 8. For the whole sample, the average loan dependence amounts to 7% of total cost across sampled firms, ranging from 3% in Azerbaijan to 13% in Kazakhstan. Notice that the standard deviations are larger than the means of loan dependence across the board, indicating that the distribution of the loan dependence variable is right-skewed: most of the data points are located on the high. This remains unchanged when we evaluate these statistics for sub-samples based on firm size and export participation.

The last column of Table 3 contains information on the share of firms with disbursed bank loans during the study period. Across the whole sample of 1415 manufacturing firms, 806 firms (57% of sample) had bank loans during the period under consideration; indicating that more than half of our sample relied on external finance.

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[33] See Appendix A for a full list of variables and definitions.

[34] The WBES is a stratified random sample survey of a representative sample of manufacturing and service firms across the private sectors of covered countries. The resulting sample covered in Table 8 is based on data availability in the WBES as countries not covered by the WBES are unavoidably omitted from our micro analysis.

Table 8: Distribution of bank loan dependence.

Sample	Mean	Std. Dev.	# of firms	% with loans
Whole sample	**0.071**	**0.198**	**1415**	**57%**
Azerbaijan	0.025	0.107	88	14%
Brazil	0.101	0.183	452	78%
Cote d' Ivoire	0.133	0.287	36	86%
Nigeria	0.043	0.180	60	27%
Indonesia	0.041	0.176	406	51%
Kazakhstan	0.082	0.312	81	25%
Mexico	0.067	0.193	189	58%
Russia	0.086	0.250	103	52%
By firm size				
Large	0.090	0.225	437	71%
Small	0.064	0.187	978	50%
Exporter				
Yes	0.058	0.154	435	65%
No	0.074	0.207	980	53%

This table reports descriptive statistics for bank loan dependence across manufacturing firms in 8 countries. Loan dependence is the ratio of total bank loan to firm production cost. Columns 5 reports the percentage of firms across sampled countries that obtained a bank loan over the sample period.

The proportion of firms relying on bank loans appears fairly significant across sampled countries, with the exception Azerbaijan, where the proportion of loan-dependent firms is only 14%. In general, we also observed subsample loan dependence in terms of firm size and export participation. Across these sub-sample categories, firm loan dependence is established for 50% or more of the sampled firms. These findings indicate that a non-trivial proportion of manufacturing plants across our sampled oil-rich countries have bank loans. Hence, we can expect the pattern of bank loans across these economies to have impact on firm growth and performance. We turn now to evaluating the impact of loan dependence on firm performance.

Returns to loan dependence in the manufacturing sector

Using the WBES data above, we gauge the relationship between loan dependence and a vector of firm performance response variables, Y_{it}:

$$Y_{it} = (Turnover_{it}, Export_{it}) \quad [17]$$

where $Sales_{it}$ is total market sales of firm *i* in period *t*, and $Export_{it}$ is the monetary value of firm exports. These variables are given in nominal local currency units, which we (i) deflated using annual CPI values from the WDI database and (ii) converted to purchasing power parities using PPP conversion factors. All values are then normalized to 2005 base year. We evaluate the changes in the elements of Y_{it} as a function of the independent variable, loan dependence Dep_{it}:

$$Y_{it} = \alpha_1 Dep_{it} + X'_{it}\beta + \theta_i + \xi_t + \varepsilon_{it} \quad [18]$$

where $\alpha_1, \ldots, \alpha_2$ is a 2×1 vector of regression parameters that capture the relationships between Y_{it} and Dep_{it}. X'_{it} contains firm characteristics such as labour, capital, firm age and firm size. θ_i is a 2×1 vector of fixed firm effects to account for unobserved heterogeneity in performance between firms, ξ_t is a vector of time fixed effects to control for certain unobserved time trends that affect firm performance, over and above the effect the loan dependence variable. ε_{it} is a vector of idiosyncratic error terms.

We present regression results for eqn. [18] in Table 9. In general, we find that loan dependence is positively associated with firm turnover and exports, albeit the coefficients on firm exports are not significant at conventional levels. In summary, the results in Table 8 and 9 indicate that a significant percentage of manufacturing firms across sampled oil-dependent countries rely on bank loans for their operations, with positive contributions to their operating performance. Therefore, one could argue that the credit allocation pattern observed in this study will have serious implications for the manufacturing sector, as suggested by the Dutch disease hypothesis.

Table 9: The effect of loan dependence on firm performance.

	Sales		Export	
	1	2	3	4
Capital	0.1024***	0.0915***	0.0134	0.0193
	[0.0253]	[0.0232]	[0.0407]	[0.0284]
Labour	0.5057***	-0.098	1.0603***	0.5376*
	[0.123]	[0.3175]	[0.2788]	[0.3194]
Age	0.5890**	0.7552*	0.5323**	1.0272*
	[0.2004]	[0.3888]	[0.2652]	[0.4791]
Size	0.5996**	1.1769	0.5792*	-0.7059
	[0.3031]	[1.153]	[0.3414]	[1.0499]
Loan dependence	0.133**	0.0676*	0.0678	0.0120
	[0.0569]	[0.0390]	[0.0613]	[0.0491]
R-squared	0.32	0.15	0.08	0.03
Year dummies	Yes	Yes	Yes	Yes
Country dummies	Yes	No	Yes	No
Country_firm dummies	No	Yes	No	Yes
N	2685	2685	2697	2697

This table reports the effects of loan dependence on firm performance (total sales and export values), controlling for firm production function and characteristics. Columns 1-4 present FE estimates with and without country_firm dummies. We do not estimate IV regressions as endogeneity test statistic of 0.017 (Chi-sq. *p*-val = 0.896) indicates no endogeneity problems. Robust standard errors reported in parenthesis are clustered at country level. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels respectively.

5.6.Further estimation issues

Although we employ an IV approach where we address concerns about the endogeneity of the oil price boom measure, nonetheless, we consider two other critical issues. First, we consider the plausible case in which other RHS variables might be endogenous. Following from a battery of Durbin-Wu-Hausman endogeneity tests[35] on our RHS variables, we treat interest and exchange rates as endogenous within our model estimations. The re-estimated regression results are presented in Table 10. Again, the qualitative implications of our main findings remain intact- oil booms are associated with contraction (expansion) in manufacturing (services) share of bank loans.

[35] The test results are available from the authors upon request.

Table 10: IV regressions treating oil boom, interest and exchange rates as endogenous

	Manufacturing	Agriculture	Services
Boom	-0.0103***	-0.0111***	0.0072***
	[0.0032]	[0.0043]	[0.0021]
Deposit	0.0094**	0.0056**	-0.0009
	[0.0038]	[0.0022]	[0.0033]
Capital	0.0036***	-0.0010	0.0039***
	[0.0009]	[0.0009]	[0.0009]
Interest rate	0.1502***	0.0694***	-0.0931***
	[0.0217]	[0.0206]	[0.0209]
Exchange rate	-0.0112**	0.0023	0.0005
	[0.0055]	[0.0028]	[0.0045]
Liquidity	-0.0103***	0.0012	0.0048***
	[0.0013]	[0.0010]	[0.001]
Size	-0.0097***	-0.0019**	0.0028**
	[0.0012]	[0.0008]	[0.0011]
OPEC	0.0929***	0.0083***	-0.0490***
	[0.0055]	[0.0011]	[0.0032]
Institutions	0.0039***	-0.0003	-0.0065***
	[0.0008]	[0.0003]	[0.0007]
R-squared	0.54	0.84	0.42
Month dummies	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes
Country dummies	Yes	Yes	Yes
Under id test: KP LM statistic	33.82	8.70	33.82
	[0.000]	[0.013]	[0.000]
Cragg-Donald Statistic	18.128	11.747	18.128
Over id test: Hansen J statistic	0.043	2.29	0.06
	[0.86]	[0.13]	[0.81]
Instrument	Weather	Weather	Oil rig & cost
N	2180	2193	2180

This table reports robustness tests of oil price boom and credit using an alternative instrumental variables model specification with the RHS variables lagged one quarter (i.e. 3 months). The dependent variables are analogous to those in Table 3 and7. Kleibergen–Paap weak and underidentification LM and Wald tests are conducted under the null hypotheses that model is weakly identified and underidentified. For the weak id test, 10% maximal IV critical value in parentheses. For the under-id test, Chi p-values are reported in parentheses. Hansen test statistic of the over-identifying restrictions is asymptotically chi-square distributed under the null of instrument validity; *p*-values are reported in parentheses. Heteroskedasticity-robust standard errors reported in parenthesis are clustered for countries. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels respectively.

Secondly, we consider an alternative model specification where all RHS variables are lagged on a quarterly basis (i.e. 3 months) to further mitigate concerns of reverse causality. This approach is particularly appealing, since credit allocation decisions might rely on previous information on specified regressors. These re-estimated IV regressions are given in

Table 11. Notice that, as in previous regressions, credit share contraction (expansion) in the manufacturing/agricultural (services) is associated with oil price booms; underpinning our previous findings.

Table 11: Alternative model specification with independent variables are lagged one quarter

	Manufacturing	Agriculture	Services
$Boom_{t-3}$	-0.0086***	-0.0085**	0.0060***
	[0.0026]	[0.0042]	[0.0017]
$Deposit_{t-3}$	0.0075**	0.0056***	0.0009
	[0.0037]	[0.0019]	[0.0035]
$Capital_{t-3}$	0.0016*	-0.0018**	0.0036***
	[0.0009]	[0.0008]	[0.0010]
$Interest_{t-3}$	0.1164***	0.0630***	-0.0840***
	[0.0164]	[0.0149]	[0.0197]
$Exchange_{t-3}$	-0.0126**	-0.0018	0.0008
	[0.0051]	[0.0024]	[0.0041]
$Liquidity_{t-3}$	-0.0118***	0.0004	0.0052***
	[0.0012]	[0.0012]	[0.0010]
$Size_{t-3}$	-0.0089***	-0.0022***	0.0025**
	[0.0012]	[0.0010]	[0.0011]
$OPEC_{t-3}$	0.0924***	0.0086***	-0.0490***
	[0.0053]	[0.0010]	[0.0031]
$Institutions_{t-3}$	0.0049***	-0.0003	-0.0068***
	[0.0010]	[0.0003]	[0.0007]
R-squared	0.56	0.37	0.44
Month dummies	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes
Country dummies	Yes	Yes	Yes
Under id test: KP LM statistic	37.28	7.78	37.28
	[0.000]	[0.0204]	[0.000]
Weak id test: KP LM statistic	20.68	3.468	20.68
	[19.93]	[19.93]	[19.93]
Over id test: Hansen J statistic	0.002	3.96	0.043
	[0.97]	[0.05]	[0.83]
Instrument	Weather	Oil rig & cost	Weather
N	2154	2154	2154

This table reports robustness tests of oil price boom and credit using an alternative instrumental variables model specification with the RHS variables lagged one quarter (i.e. 3 months). The dependent variables are analogous to those in Table 3 and 7. Kleibergen-Paap (2006) weak and underidentification LM and Wald tests are conducted under the null hypotheses that model is weakly identified and underidentified. For the weak id test, 10% maximal IV critical value in parentheses. For the under-id test, Chi p-values are reported in parentheses. Hansen test statistic of the over-identifying restrictions is asymptotically chi-square distributed under the null of instrument validity; *p*-values are reported in parentheses. Heteroskedasticity-robust standard errors reported in parenthesis are clustered for countries. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels respectively.

6. Concluding remarks and policy implications

Banks play key functions in every economy by screening investment projects and allocating capital accordingly. As Stiglitz (1993) argued, if they fail in these functions, the costs and implications to the economy are huge. It is therefore imperative to investigate the extent to which banking systems in resource rich countries efficiently allocate or intermediate resources during commodity booms. This question has become critical to our understanding of the linkages between the level of financial development and resource dependence. It is no less important for our understanding of the extent to which banks (fail to) intermediate these booms, as little is known about bank credit allocation behaviour during commodity price booms. Using banking sector-level data for a sample of 13 oil producing countries, we provide the first comprehensive analysis of the effects of commodity booms on sectoral credit allocation.

Our results show that the pattern of sectoral credit allocation during commodity booms are symptomatic of the Dutch disease- manufacturing (services) sector share of bank lending shrinks (expands) during periods of oil booms. Given these findings, we robustly reject the null hypotheses that banks play a role in countervailing the Dutch disease through their credit screening and efficient intermediation function. Consequently, we argue that credit allocation patterns during oil booms potentially constitute a channel through which the Dutch disease syndrome stagnates tradeable sector investments and productivity performance.[36] This pattern is also consistent with the view of a financial resource curse (Beck, 2011). These findings are robust to a battery of robustness checks such as an instrumental variables approach which caters to heterogeneity and endogeneity concerns; alternative measures of oil boom, quantile regressions aimed at isolating our relationship of

[36] See Benigno and Fornato (2014) for some theoretical exposition on this idea.

interest at different points in the conditional distribution of credit allocation, an alternative definition of the tradeable sector, as well as an alternative model specification.

Our results have important policy implications. First it should be clear that the strong rejection of our null hypothesis indicates that central banks across sampled countries have to take on the role of seeing beyond the boom as they cannot rely on the banks' efficient capital allocation business to carry out countervailing policies. This appears consistent with the arguments by Benigno and Fornato (2014) for some form of interventions in the flow of productive resources across the economy in order to mitigate the misallocation of resources during an episode of financial resource curse.[37] This idea seems justified since our results indicate that the *"public good"* element of the banking system credit allocation might be inadequate to countervail the resource curse.

While our study constitutes the first comprehensive analysis of sectoral credit allocation across banking systems of oil rich countries, we recognize that the findings of this study may not apply to other commodity classes. Hence, it is hoped that future studies will aim to understand the behaviour of credit patterns during booms of other commodity types. Furthermore, it would also be interesting to place our results in the context of future research relying on alternative methods. In the long run, this would contribute to the evolution of a rich array of identification strategies for evaluating credit patterns arising from commodity booms. Also, future analogous analyses using bank-level data are required to investigate micro-level bank lending behaviour during commodity booms. Such microeconomic analyses will also allow for the disentangling of bank-level behaviour from other macro effects. However, we note the difficulty arising from the lack of suitable microdata on bank-level

[37] As Gylfason (2006) argues, resource based economies can efficiently use resources/revenues from windfalls as buffer to smooth consumption over the *boom-burst* cycles that are prevalent in oil price movements.

sectoral lending spanning a reasonably long period[38] to conduct a meaningful analysis of commodity price shocks.

Finally, theoretical and empirical arguments indicate different channels through which the Dutch disease syndrome impacts the economy. These channels include (i) trade/exchange rate channel (ii) spending effects and (iii) weak institutions. It is possible to test these channels along with the use of bank-level data. For instance, it would be interesting to unravel the channels through which commodity booms shape bank credit policies in the context of (i) foreign asset exposure (ii) market power and (iii) management quality. These bank-level channels are rough analogues of the macro-level channels above.

[38] For instance, Bureau Van Dijk's major bank database Orbis Bank Focus which succeeds the legacy Bankscope database has only contains 6 years' history for listed banks and 4 years for unlisted.

References

Acemoglu, D. and Robinson, J., 2010. The Role of Institutions in Growth and Development. *Review of Economics and Institutions*, *1*(2).

Agarwal, I., Duttagupta, R., & Presbitero, A., 2017. Commodity prices and bank lending in low-income countries. *Unpublished manuscript*.

Agnello, L. and Schuknecht, L., 2011. Booms and busts in housing markets: determinants and implications. *Journal of Housing Economics*, *20*(3), pp.171-190.

Beck, T. 2011. “Finance and Oil: Is There a Natural Resource Curse in Financial Development?” In: Rabah Arezki, Thorvaldur Gylfason and Amadou Sy (Eds.): *Beyond the Curse: Policies to Harness the Power of Natural Resources*, Washington DC: IMF, pp.81-106.

Beck, T. 2016. Finance, institutions and development: literature survey and research agenda EDI working paper series WP16/7.

Beck, T., Demirgüç-Kunt, A.S.L.I. and Maksimovic, V., 2005. Financial and legal constraints to growth: Does firm size matter?. *The Journal of Finance*, 60(1), pp.137-177.

Beck, T. and Poelhekke, S. 2017. Follow the money: Does the financial sector intermediate natural resource windfalls? De Nederlandsche Bank Working Paper No. 545.

Benigno, G. and Fornaro, L., 2014. The financial resource curse. *The Scandinavian Journal of Economics*, 116(1), pp.58-86.

Bernanke, B., Gertler, M. and Gilchrist, S., 1996. The Financial Accelerator and the Flight to Quality. *The Review of Economics and Statistics*, *78*(1), pp.1-15.

Bjørnland, H.C., 2009. Oil price shocks and stock market booms in an oil exporting country. *Scottish Journal of Political Economy*, *56*(2), pp.232-254.

Borenstein, S., Cameron, A.C. and Gilbert, R., 1997. Do gasoline prices respond asymmetrically to crude oil price changes?. *The Quarterly Journal of Economics*, 112(1), pp. 305-339.

Cetorelli, N. and Gambera, M., 2001. Banking market structure, financial dependence and growth: International evidence from industry data. *The Journal of Finance*, *56*(2), pp.617-648.

Collier, P., van der Ploeg, F., Spence, M., Venables, A.J., 2009. Managing resource revenues in developing economies. *IMF Staff Papers* 57 (1), pp. 84-118.

Combes, J-L., C.H. Ebeke, S.M.N. Etoudi, and T.U. Yogo, 2014. Are Remittances and Foreign Aid a Hedge Against Food Price Shocks in Developing Countries? *World Development*, 54, pp. 81-98.

Corden, W.M., 1984. Booming sector and Dutch disease economics: survey and consolidation. *Oxford Economic Papers*, *36*(3), pp.359-380.

Corden, W.M. and Neary, J.P., 1982. Booming sector and de-industrialisation in a small open economy. *The Economic Journal*, *92*(368), pp.825-848.

Deaton, A., and R. Miller 1995, International Commodity Prices, Macroeconomic Performance, and Politics in Sub-Saharan Africa. Princeton, NJ: Princeton Studies in International Finance, No 79.

Galindo, A. and Micco, A., 2004. Do state owned banks promote growth? Cross-country evidence for manufacturing industries. *Economics letters*, 84(3), pp.371-376.

Gately, D., Huntington, H. G. (2002) The asymmetric effects of changes in price and income on energy and oil demand. *Energy Journal*, 23(1), pp. 19-55

Griffin J. M., Schulman C. T. (2005) Price asymmetry in energy demand models: A proxy for energy-saving technical change? *Energy Journal*, 26(2), pp. 1-21.

Heller, P.S. and Gupta, S., 2002. Challenges in expanding aid flows. *Finance and Development*, 39(2), pp.40-43.

Gylfason, T., 2006. Natural resources and economic growth: From dependence to diversification. *Economic Liberalization and Integration Policy*, pp.201-231.

Gylfason, T. and Zoega, G., 2006. Natural resources and economic growth: The role of investment. *The World Economy*, *29*(8), pp.1091-1115.

Hamilton, J., 1989. A New Approach to the Economic Analysis of Nonstationary Time Series and the Business Cycle. *Econometrica*, 57(2), pp. 357-384

Hamilton, J.D., 1996. This is what happened to the oil price-macroeconomy relationship. *Journal of Monetary Economics*,38(2), pp. 215-220.

Hamilton, J.D., 2009. Causes and consequences of the oil shock of 2007-08. *Brookings Papers on Economic Activity*, Spring 2009, pp. 215-259.

Hansen, L. 1982. Large sample properties of generalized method of moments estimators. *Econometrica*, 50(3), pp. 1029-1054.

Hawkins, P., 2006. Financial Access and Financial Stability. BIS www.bis.org/press/p060619.htm

Im, K. S., M. H. Pesaran, and Y. Shin, 2003. Testing for unit roots in heterogeneous panels. *Journal of Econometrics*, 115(1), pp. 53-74.

Ismail, K., 2010. The structural manifestation of the “Dutch disease”: the case of oil-exporting countries. International Monetary Fund Working Paper 10/103, Washington, D.C.

Jaeger, A. and Schuknecht, L., 2007. Boom-bust phases in asset prices and fiscal policy behavior. *Emerging Markets Finance and Trade*, *43*(6), pp.45-66.

Jaffee, D. and Stiglitz, J., 1990. Credit rationing. *Handbook of Monetary Economics*, 2, pp.837-888.

Kaufmann, D., Kraay, A., Mastruzzi, M., 2010. The Worldwide Governance Indicators: A Summary of Methodology, Data and Analytical Issues. World Bank Policy Research Working Paper 5430

Kilian, L., 2009. Not all oil price shocks are alike: Disentangling demand and supply shocks in the crude oil market. *The American Economic Review*, 99(3), pp.1053-1069.

Kinda, T., Mlachila, M. and Ouedraogo, R., 2016. Commodity price shocks and financial sector fragility. IMF Working Paper WP/16/12.

Kleibergen, F., Paap, R., 2006. Generalized reduced rank tests using the singular value decomposition. *Journal of Econometrics* 133(1), 97-126

Lin, C.Y.C., 2008. Estimating supply and demand in the world oil market. *The Journal of Energy and Development*, 34(1/2), pp.1-32.

Manski, C.F., 2003. Identification problems in the social sciences and everyday life. *Southern Economic Journal*, 70(1), pp. 11-21

Mansoorian, A., 1991. Resource discoveries and 'excessive' external borrowing. *The Economic Journal*, 101 (409), pp.1497-1509

Mehlum, H., Moene, K. and Torvik, R., 2006. Institutions and the resource curse. *The Economic Journal*, 116(508), pp.1-20.

Morice, C.P., Kennedy, J.J., Rayner, N.A. and Jones, P.D., 2012. Quantifying uncertainties in global and regional temperature change using an ensemble of observational estimates: The HadCRUT4 data set. *Journal of Geophysical Research*: Atmospheres, 117(D8).

Musayev, V., 2014. Commodity Price Shocks, Conflict and Growth: The Role of Institutional Quality and Political Violence.

Neary, J.P. and D.D. Purvis (1982). Sectoral shocks in a dependent economy: long-run adjustment and short-run accommodation, *Scandinavian Journal of Economics*, 84(2), pp. 229-253.

North, D.C., 1994. Economic performance through time. *The American Economic Review*, *84*(3), pp.359-368.

Peek, J. and Rosengren, E., 1995. The capital crunch: Neither a borrower nor a lender be. *Journal of Money, Credit and Banking*, 27(3), pp.625-638.

Pesaran, M.H., 2007. A simple panel unit root test in the presence of cross-section dependence. *Journal of Applied Econometrics*, *22*(2), pp.265-312.

Plante, M. and Dhaliwal, N., 2017. Inventory shocks and the oil-ethanol-grain price nexus. *Economics Letters*, 156, pp.58-60.

Rajan, R.G., 1994. Why bank credit policies fluctuate: A theory and some evidence. *The Quarterly Journal of Economics*, 109(2), pp.399-441.

Rajan, R.G. and Zingales, L., 1998. Financial Dependence and Growth. *The American Economic Review*, 88 (3), pp. 559-586.

Robinson, J.A., Torvik, R. and Verdier, T., 2006. Political foundations of the resource curse. *Journal of Development Economics*, *79*(2), pp.447-468.

Sargan, J. 1958. The estimation of economic relationships using instrumental variables. *Econometrica*, 26(3), pp. 393-415.

Setser, B.W. and Frank, C.V., 2017. Using External Breakeven Prices to Track Vulnerabilities in Oil-Exporting Countries. Greenberg Center for Geoeconomic Studies, Discussion Paper, Council on Foreign Relations (CFR)

Stiglitz, J.E., 1993. The role of the state in financial markets. *The World Bank Economic Review*, 7(suppl_1), pp.19-52.

Stiglitz, J.E. and Weiss, A., 1981. Credit rationing in markets with imperfect information. *The American Economic Review*, 71(3), pp.393-410.

Van der Ploeg, F. and Poelhekke, S., 2009. Volatility and the natural resource curse. *Oxford Economic Papers*, 61(4), pp.727-760.

Van der Ploeg, F. and Venables, A.J., 2013. Absorbing a windfall of foreign exchange: Dutch disease dynamics. *Journal of Development Economics*, 103, pp.229-243.

Wang, Y., Wu, C. and Yang, L., 2013. Oil price shocks and stock market activities: Evidence from oil-importing and oil-exporting countries. *Journal of Comparative Economics*, 41(4), pp.1220-1239.

Westernhagen, N., E. Harada, T. Nagata, B. Vale, J. Ayuso, J. Saurina, S. Daltung, S. Ziegler, E. Kent, J. Reidhill, and S. Peristiani (2004). Bank failures in mature economies. Basel Committee on Banking Supervision Working Paper 13

Wu, T. and Cavallo, M., Measuring Oil-Price Shocks Using Market-Based Information. *Journal Issue*, 2012, p.19.

Wu, T., McCallum, A., 2005. Do oil futures prices help predict future oil prices? *FRBSF Economic Letter* no. 2005-38.

Yuxiang, K. and Chen, Z., 2011. Resource abundance and financial development: Evidence from China. *Resources Policy*, 36(1), pp.72-79.

Appendix A

Table A1: Variables definitions and data sources

Variable	Definition	Source
Banking sector-level data		
Agriculture share of credit	Ratio of banking sector loan to agricultural sector to total loans	Monthly central bank statistical bulletins, several
Manufacturing sector share of credit	Ratio of total banking sector loan to manufacturing sector to total loans	Monthly central bank statistical bulletins, several
Service sector share of credit	Ratio of total banking sector loan to services sector to total loans	Monthly central bank statistical bulletins, several
Oil price boom	Spot oil price deviations from forecast prices	EIA
Real interest rate	Average monthly lending rate	Monthly central bank statistical bulletins, several
Total deposits	Total value of banking sector deposits, including private and public-sector deposits	Monthly central bank statistical bulletins, several
Total capital	Total value of equity capital in the banking sector	Monthly central bank statistical bulletins, several
Real exchange rate	Real effective exchange rate (REER)	IMF-IFS
Liquidity	Ratio of broad money (M2) to international reserves	Monthly central bank statistical bulletins, several
Banking sector size	Total banking sector assets	Monthly central bank statistical bulletins, several
OPEC	Dummy variable equal to 1 if the country is a member of OPEC, zero otherwise	Authors' calculation
Institutional quality index	Constructed by applying principal component analysis to World Governance indicators	Kaufmann et al. (2010)
Instrumental variables		
Variable cost per barrel of oil in the US	US oil sector: (Total man hours * hourly wage * total oil produced)/(volume of oil produced)	U.S. Bureau of Labor Statistics and EIA
Global temperature	Monthly average global temperature	U.K. Met Office
Total world oil rigs	Count of operational oil rigs across the world	Baker Hughes, Inc. database
Firm-level data		
Sales	Total value of firm sales	WBES
Export	Total value of firm sales for export	WBES
Capital	Net book value of buildings and equipment	WBES
Labour	Total number of employees	WBES
Age	Firm age derived as operating year minus date of birth	WBES
Size	WBES Firm size classification	WBES
Loan dependence	Ratio of firm total loan value to operating cost	WBES

Supplementary variables		
Consumer price index (CPI)	Monthly consumer price indices	IMF-IFS
PPP conversion factors	PPP conversion factor, GDP (LCU per international $)	WDI
Country weights for boom	Fuel exports (% of merchandise exports)	WDI
Country weights for instruments	Country oil reserves (% of global oil reserves)	BP Annual Statistical Bulletin

Appendix B

Table B1: Panel unit root tests

	IPS		CIPS	
	Statistic	p value	Statistic	p value
Boom	-11.76*	0.000	-11.584*	0.000
Manufacturing	-5.17*	0.000	-5.338*	0.000
Services	-4.975*	0.000	-6.570*	0.000
Exchange rate	0.064	0.526	-1.436	0.076
Interest rate	-5.611*	0.000	-9.527*	0.000
Deposit	-3.772*	0.000	-3.916*	0.000
Capital	-4.225*	0.000	-5.920*	0.000
Liquidity	-7.8554 *	0.000	-9.8834*	0.000
Size	-0.158	0.437	-3.980*	0.000

Notes: IPS refers to the panel unit root test of Im, Pesaran, and Shin (2003) and CIPS refers to the panel unit root test of Pesaran (2007) which accounts for cross-sectional dependence among sampled countries. *Rejection of the null hypothesis at 5% significance level. The 5% critical value for the IPS statistics is -1.730 and the 5% critical value for the CIPS statistics is -2.120

Table B2: Relationship between oil price boom and instruments

	1	2	3
Temperature	4.510***		
	[0.684]		
Oil rigs		0.001***	
		[0.000]	
Variable cost			0.037***
			[0.005]
Constant	0.988***	0.955***	0.786***
	[0.182]	[0.178]	[0.173]
R-sqr	0.43	0.44	0.45
N	2206	2206	2206

This table presents the first stage regression of the oil price boom on employed instruments. Heteroskedasticity-robust standard errors are presented in brackets. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels respectively

Appendix C

Construction of institutional quality variable

Our institutional quality measure is constructed by applying principal component analysis (PCA) to the World Governance indicators (WGI) (Kaufmann *et al*., 2010). The indicators cover six dimensions: (i) Voice and accountability (ii) Political stability (iii) Government effectiveness (iv) Regulatory quality (v) Rule of law and (vi) Control of corruption. One the one hand using only one dimension of the WGI (e.g. iv: regulatory quality) might prove inadequate in capturing the quality of institutions across sampled counties. On the other hand, including all five dimensions in the same regression poses the challenge of multicollinearity. Consequently, the PCA is a sensible compromise that eliminates the potential multicollinearity between the WGI dimensional measures, while also boosting the precision and efficiency of model estimations by reducing the number of RHS variables.

We use PCA to combine the six above mentioned WGI components to create a parsimonious composite institutional quality variable (i.e., principal components) by filtering out redundancies in the original indicators, while retaining the underlying variation in the original series. The resulting composite variable employed in our regressions "Comp1" captures the common variation among the WGI indicators, as demonstrated by its eigenvalue of 4.27>1, as well accounting for 71% variation (see table C1).

Table C1: Principal Component Analysis (PCA)

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	4.279	3.270	0.713	0.713
Comp2	1.009	0.620	0.168	0.881
Comp3	0.389	0.219	0.065	0.946
Comp4	0.170	0.087	0.028	0.975
Comp5	0.083	0.012	0.014	0.988
Comp6	0.071	-	0.012	1

Although our analysis is based on monthly data, the institutional variable has an annual frequency, so we repeat the annual values for all 12 months in the corresponding year. This approach seems consistent with the fact that quality of economic and political institutions is likely to have an attribute of persistence: i.e. changes are gradual or relatively slow-changing (North, 1994; Acemoglu and Robinson, 2010).

Appendix D

Figure D1: Key events and the evolution of real oil prices