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Let beholders behold: Can banks see beyond oil booms and mitigate the Dutch disease?[#]

Morakinyo O. Adetutu [a†], John E. Ebireri[a] , Victor Murinde[b] and Kayode A. Odusanya[a]

ABSTRACT

While the potential role of oil booms in crowding out the tradable sector is well documented in the Dutch disease literature, the potential contribution of bank lending behaviour to the oil resource curse syndrome remains largely unexplored. In this paper, we investigate contrasting variations in bank credit flows to the tradable (manufacturing) and non-tradable (service) sectors, across 14 oil-rich economies during 1994-2017, in order to shed light on whether bank lending behaviour mitigates or accentuates the syndrome. We uncover new evidence of significant contraction in the manufacturing sector share of bank credit during oil booms, while the service sector share of bank lending expands. Overall, our results are robust to alternative tests and unequivocally reject the hypothesis that banks can see beyond oil booms by allocating credit across sectors in a manner that mimics countervailing monetary policy to intermediate oil windfalls and mitigate the Dutch disease. Rather, bank sectoral credit allocation accentuates the Dutch disease by crowding out the tradable sector.

Keywords*:* Dutch disease, sectoral credit allocation, oil price boom, manufacturing sector, oil resource curse, service sector

JEL Classification*:* C23; D22; E44; G21

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1. Introduction

One common explanation for the poor economic performance of resource-rich economies is the so-called Dutch disease which refers to the adverse effects of a natural resource boom on the tradable sector (see, for example, Papyrakis, 2017). The explanation follows from the seminal proposition by Corden and Neary (1982), which attributes the contraction of the tradable sector to the sharp inflow of extra foreign currency arising from a resource boom[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. While the large literature on the Dutch disease, or natural resource curse, embodies a range of mechanisms through which natural resource booms can impact economic performance[2], the overarching conclusion is that the tradable sector is crowded out, for example via reduced investments in the manufacturing sector (Gylfason and Zoega, 2006; Yuxiang and Chen, 2011; Mideksa, 2013; and Van Der Ploeg and Poelhekke, 2017).

The intuition behind the crowding out argument is that natural resource exploitation results in the contraction of the tradable sector by shifting productive resources toward the non-tradable sector (Krugman, 1987; Gylfason et al., 1999). In addition, the analysis by Benigno and Fornato (2014) indicates that consumption booms fueled by large income inflows often require resource shifts toward the non-tradable sector[3]. However, Allcott and Keniston (2017) present new evidence which suggests that in the US, natural resources benefit producer economies, contrary to the "Natural Resource Curse" syndrome. By combining new data on oil and gas endowments with Census of Manufactures microdata, it is found that local wages

[1] One strand of the literature provides some empirical evidence on the positive contributions of natural resource discovery and extraction towards economic growth (e.g. Sachs, 2007; Alexeev and Conrad, 2009; Mideksa, 2013). See Van der Ploeg and Poelhekke (2017) for a comprehensive and balanced review of the large Dutch disease literature.

[2] For example, exchange rate effects, weak institutions, rent seeking and corruption, armed conflicts.

[3] Benigno and Fornato (2014) focus on financial resource curse arising from large capital inflows triggered by falling interest rate; this is analogous to the sharp income inflow arising from a natural resource boom.

rise during oil and gas booms, but manufacturing is not crowded out, rather the sector grows overall, driven by upstream and locally-traded subsectors.

It may well be the case that, in the light of new evidence which challenges the received wisdom about the Dutch disease associated with oil booms, there are good grounds for exploring additional factors that may explain resource shifts from the tradable to the non-tradable sector or otherwise. Interestingly, in a recent critical survey of the natural resource curse, Badeeb et al. (2017) call for new research that explores mechanisms through which natural resources affect economic outcomes, especially by considering factors closely associated with economic growth. Similarly, Beck (2016) highlights that the linkages between natural resource exploitation and financial sector development remain under-researched. For example, the existing literature is unable to shed much light on the hitherto unexplored but pertinent questions regarding the role of the financial system in sectoral resource shifts in response to natural resource booms. To the best of our knowledge, there is no direct empirical evidence on whether (and the extent to which) the pattern of bank credit flows to tradable and non-tradable sectors of oil- producing economies might contribute to the Dutch disease.

Indeed, the role of the financial sector in these sectoral shifts remains unclear. In particular, two observations can be inferred from the sparse literature exploring the linkages between commodity markets and financial systems. The first observation suggests the existence of a natural resource curse in the financial sectors of resource-rich countries (e.g. Van der Ploeg and Poelhekke, 2009; Beck, 2011; Beck and Poelhekke, 2017). The point here is that low levels of financial development is a consequence of resource abundance. A second observation attempts to associate financial sector instability with negative commodity price shocks (e.g. Kinda et al., 2016; Agarwal et al., 2017).

Nevertheless, since it is well established in the literature that well-functioning banking systems ensure efficient capital allocation by channeling funds to the most productive investment projects towards stimulating economic growth (Levine, 1997; 2005), and given the resource shifts required for the Dutch disease to occur, it becomes crucial to investigate whether (and the extent to which) the financial system contributes to the Dutch disease syndrome. Do sectoral lending patterns accentuate or mitigate the crowding-out of the tradable sector? To what extent do banks in oil-rich countries countervail the Dutch disease through their credit screening and efficient intermediation function? Do banks *see beyond* oil price booms?

In this paper, we investigate the direct empirical relationship between oil booms and bank lending behaviour. We fill an important gap in the literature, by focusing on the sectoral credit allocation role of banks in the Dutch disease syndrome. Specifically, our contribution to existing literature is threefold. Firstly, we open a new line of enquiry into bank behaviour during commodity booms. The analysis of sectoral credit flows during commodity booms could offer rare insight into the potential role of credit markets in mitigating the Dutch disease. Our underlying intuition is that, through intermediation and efficient capital allocation, banks can *see beyond the oil boom*[4], and hence behave as if they were implementing countervailing monetary policies that smoothen economic performance over oil boom cycles towards avoiding the Dutch disease. From a policy point of view, this issue is strategically important because of the need to determine if monetary authorities can rely on banks' efficient capital allocation business to carry out countervailing policies.

Secondly, bank credit allocation patterns in resource-rich countries could provide useful information on the strategic response of banks to commodity price movements. We argue that the strategic lending behaviour by banks during commodity booms is an implicit indicator of financial development across these economies. Intuitively, if the financial systems in these countries adequately play their efficient credit allocation role, there is great potential

[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.

for them to countervail the Dutch disease syndrome by slowing the rate of resource shifts from the tradable sector.[5] In short, we suggest that the extent to which sectoral bank credit flows are decoupled from commodity market procyclicality is an implicit indicator of financial system development across resource-rich economies. It is also a measure of the potential resilience of the macroeconomy to adverse commodity shocks.

Thirdly, because this study employs disaggregated 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 bank credit to the consumption driven non-tradable 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 bank credit access, relative to other firms or sectors. Moreover, given that many resource-dependent countries are developing economies, the macroeconomic implications of unfavorable bank credit allocation to tradable sectors are huge because productivity grows faster in the main tradable sectors (i.e. manufacturing and agriculture), relative to the non-tradable sector (Duarte and Restuccia, 2010; Benigno and Fornato, 2014).[6]

Using monthly sectoral bank loan data for a sample of 14 oil producing countries over the period 1994-2017, we empirically test the hypothesis that banks intermediate oil windfalls by allocating credit as if they were conducting countervailing monetary policy to mitigate the Dutch disease. Specifically, we investigate the relationship between sectoral bank credit shares and oil price booms using an instrumental variables (IV) approach that addresses the potential

[5] This line of argument crucially speaks to the assumption that banks can *see beyond* the commodity boom, perhaps because the accompanying consumption boom that fuels the non-tradable sector growth are driven by largely unpredictable and volatile commodity price trends.
[6] Benigno and Fornato (2014) demonstrate that, due to their superior scope for productivity gains, the tradable sector is mainly the engine of growth of the economy. Hence, resource reallocation away from the tradable sectors will slow down technology absorption and result in periods of low overall productivity growth.

endogeneity of oil price booms arising from country-specific events that impact oil markets. We uncover new evidence that oil booms are associated with contraction (expansion) in manufacturing (service) sector share of bank credit. These findings remain robust after a battery of sensitivity tests such as accounting for country-specific effects, addressing endogeneity concerns, employing alternative measures of oil booms, and conducting a microeconometric case study using bank-level data for the entire Kazakh banking industry.

Overall, we reject the hypothesis that banks can *see beyond oil booms* by allocating credit as if they were implementing countervailing monetary policy against the Dutch disease. The implication of our results is that the sectoral bank credit allocation pattern is potentially a channel through which productive resources are shifted toward the non-tradable sector at the expenses of the tradable sector. Hence, public policy authorities across the sample countries have to take on the role of seeing beyond the oil boom as they cannot rely on the banks' efficient capital allocation business to carry out countervailing policies. The findings from our microeconometric case study of Kazakh banks underscores this point of view.

The remainder of the paper is structured into five parts. Section 2 discusses the related literature and highlights the gap that this paper attempts to fill. In Section 3, we provide a theoretical framework to underpin our empirical model. The model is presented in Section 4, together with discussion of estimation and testing procedures. Section 5 describes the data and descriptive statistics. In particular, we discuss in detail some potential measurement issues implicit in deriving a measure of oil price booms. Section 6 discusses the empirical results, along with robustness and sensitivity tests on the impact of oil booms on bank credit patterns. Section 7 offers the conclusion of the study and highlights the key policy implications.

2. Related literature

While the economics literature features important contributions to our understanding of the Dutch disease phenomenon, a relatively under-researched area relates to the importance of financial development for natural resource rich countries (Beck, 2016). A critical issue is whether financial the financial sector plays a role in amplifying or mitigating the Dutch disease problem, especially regarding the role of banks in allocating oil windfalls during periods of commodity shocks. Two strands of the literature are relevant here. The first theme suggests the existence of a natural resource curse in the financial sectors of resource-rich countries (e.g. Van der Ploeg and Poelhekke, 2009; Beck, 2011; Yuxiang and Chen, 2011; Bhattacharyya and Hodler, 2013; Kurronen, 2015; and Beck and Poelhekke, 2017). Findings in this literature appear to be consistent with the view that a causal relationship exists between resource abundance, resource dependence and financial development. For instance, Samargandi et al., (2014) and Allegret et al., (2014) find that a healthy financial system lowers the effect of commodity volatility[7]. Similarly, Yuxiang and Chen (2011) show that resource-rich provinces in China experience a slower pace of financial development than resource-poor provinces, indicating a negative relationship between resource abundance and financial development. This finding is consistent with Bhattacharyya and Hodler (2013) and Beck and Poelhekke (2017) who found a negative impact of natural resource revenues on financial development when political institutions are weak. In addition, Kurronen (2015) provides empirical evidence to show that banking sectors in resource-dependent economies tend to be smaller, supporting the view by Lin et al. (2009) that financial systems are expected to reflect the production structure of the economy and suggesting that large firms in the dominant resource-based sectors are expected to benefit more.

[7] Nili and Rastad (2007), Beck (2011), Cespedes and Velasco (2012), Samargandi et al. (2014) and Allegret et al. (2014) are some studies that come up with similar findings.

A second but sparse strand of the relevant literature explores the impact of negative commodity shocks on bank health in resource rich economies, e.g. credit growth (Agarwal, et al., 2017), as well as on financial sector stability (Kinda et al., 2016). More specifically, Kinda et al., (2016) examine the impact of commodity price shocks on financial fragility and show that negative shocks to commodity prices may increase financial sector fragility as well as increasing the possibility of systemic banking crises. Along similar lines, Agarwal et al. (2017) examine how the banking sector, through its financial intermediary and lending activities, transfers the impact of commodity price changes to the real economy. They show the adverse effects of commodity price shocks on bank lending, particularly for low income countries and countries that are natural resource-dependent.

While the above strands of the literature examine the impact of resource abundance on financial development and explore the implications of commodity price shocks on the financial sector, it remains unclear whether a reverse-causal effect runs from the financial sector to the occurrence of the Dutch disease. This study directly investigates bank lending behaviour during oil price booms in order to unravel the extent to which this bank behavior may contribute to the Dutch disease. Unlike previous studies that treat the level of financial sector development as a consequence of resource abundance or commodity shocks, we explore the reverse implication of bank credit allocation behaviour on the Dutch disease.

3. Analytical framework

3.1. Theoretical considerations

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 the booming sector *B* (i.e. oil sector) and the lagging tradable sector *L* (e.g. manufacturing sector). In this framework, we assume that output in each sector requires sector-specific capital and labour[8]. In line with previous studies (e.g. Beck, 2011), 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*.

3.2. Bank credit policy and resource allocation

We start addressing the potential contribution of bank lending behavior to the factor shifts described above. We seek to analyze the relationship between bank credit allocation and oil booms. Our main task is to demonstrate whether bank credit policies are correlated with oil booms across the sample countries. 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 has two assets, credit or loans (*C*) and securities such as treasury bills (A); and two types of liabilities, namely capital (*K*) and deposits (*D*), so we write the linear balance sheet constraint (suppressing subscripts and 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. 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):

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

[8] Labour is assumed to be mobile across the three sectors, towards equalizing wages.

One critical attribute of the analysis above is that the size of π is a function of the efficiency or quality of the bank's credit allocation which directly influences δ, a measure of uncertainty or *bad loan* outcome. Hence, banks must perform a screening function to distinguish between good and bad risks in order to maximize π. This leads us to postulate 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[9] which allows us to motivate our empirical credit allocation model as more of a supply schedule than a demand model. In this supply decision model, the financial system has to screen loan applications and ration credit.

3.2.1. Credit allocation as a public good

We assume 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 there is scope for imperfect or asymmetrical information[10] and uncertainty which is embodied in δ. Hence, Jaffee and Stiglitz (1990) suggest that bank screening functions are front and center in the banking system allocation function. It is argued 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 or sectoral conditions may be managed and mitigated in ways that the overall return to the society or 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

[9] See Stiglitz and Weiss (1981) for a classic treatment of credit rationing by banks.
[10] 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

Stiglitz's (1993; pp.23) view on the resource allocation role of banks 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*"[11].

4. Empirical strategy

4.1. The empirical model

Following from the literature survey in Section 2 and the theoretical idea on bank screening and allocation functions in Section 3, we hypothesize as follows:

- *H_0. Banks see beyond oil booms by allocating credit as if they were conducting countervailing monetary policy to intermediate oil windfalls and mitigate the Dutch disease;*
- *H_A. Bank sectoral credit allocation accentuates the Dutch disease by crowding out tradable sectors.*

The null hypothesis (H_0) and the alternative hypothesis (H_A) derive from the Dutch disease phenomenon, such that they could help deepen our understanding of how banks' lending behavior in resource rich economies contribute to amplifying or mitigating the Dutch disease. In order to generate the testable form of the two hypotheses and empirically examine the relationship between oil price booms and sectoral credit allocation, we specify and estimate the following baseline panel data regression model:

$$C_{kit} = \alpha_0 + \alpha_1 B_{it} + \boldsymbol{\gamma} \boldsymbol{z}'_{kit} + \mu_i + \varepsilon_{it} \qquad [3]$$

where C_{kit} is the credit share of sector *k* in country *i* in period *t*, B_{it} is the oil boom variable for country *i* in time *t*, $\boldsymbol{z}'_{kit}$ is a vector of sector-specific, bank industry and macroeconomic characteristics which traditionally influence sectoral credit allocation according to the

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

literature, μ_i represents country specific effects, ε_{it} is a random error term; α_1 is our parameter of interest which measures the extent to which oil booms influence sectoral credit shares.

4.2. Instrumental variables (IV) approach

The classic problem with the estimation of [3] is the potential endogeneity of the oil boom variable. The identification of the parameters in [3] 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 between 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[12] could also influence world oil price movements (see Kilian, 2009). Also, each country in our data sample has its own economic, political, and institutional characteristics which might be correlated with other regressors in the model in [3]. 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 ε_{it} within the model, which will bias parameter estimates.

Given the discussions above on the oil demand and supply covariates along with the other model complications, we expect that the fixed and time-varying country-specific factors implicit in μ_i and ε_{it} are correlated with the boom variable B_{it} in the model [3]. Hence, this identification problem implies that ordinary least squares (OLS) methods will not yield efficient or consistent estimates of the effects of oil booms on bank lending behavior. For this matter, 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

[12] 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.

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 (see Manski, 2003).

Guided by theory and empirical evidence, we instrument for the oil boom variable using data on (i) weather (ii) world oil rig count and (iii) variable cost of oil production in the US.[13] For weather, we use the average global temperature which we take from the U.K. Met Office Hadley Centre observations datasets (Morice, *et al*., 2012). We take the world oil rig count data from Baker Hughes, Inc. database. We derive the variable cost of oil production using information on (a) oil and gas employees (b) man-hours (c) wages and (d) oil output. These series are obtained from the U.S. Bureau of Labor Statistics and the U.S. Energy Information Administration (EIA). Notice that these instruments are either global or pertain to regions outside our sampled oil-rich 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 world oil reserves (taken from the BP Annual Statistical Bulletin). This weight is appealing since it preserves the exogeneity of the resulting instruments given that oil endowment or reserves is an exogenous, naturally occurring phenomenon.

5. Data and descriptive statistics

5.1. Data sample

To investigate the relationship between sectoral allocation of credit and commodity booms, we draw on a number of data sources such as several issues of central banks' statistical bulletins, IMF International Financial Statistics (IFS), and the database of the Energy Information Administration (EIA). A detailed description of variables and data sources is presented in

[13] See Lin (2008) for some discussion.

Appendix A. We also exploit bank-level data for the entire Kazakh banking industry, obtained from the Kazakhstan Central Bank, the “National Bank of Kazakhstan”, to understand the channels through which oil booms influence bank lending behavior. Finally, we employ firm-level data on manufacturing enterprises from the World Bank Enterprise Survey (WBES) to check firm-level dependence on external finance.

[INSERT TABLE 1 HERE]

Table 1 presents key economic indicators on income, oil contribution and financial development for our sample countries using 2016 data. 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 and find that 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.

5.2. Key variables and data sources

Our final dataset contains monthly[14] information on bank credit to the manufacturing sector and the service sector across 14 oil producing countries[15] over the period 1994-2017, yielding a panel data sample of 2310 observation. We deflate all monetary values to 2012 (2012=100) prices using monthly Consumer Price Index (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. Below, we give a brief description of the key variables.

5.2.1. Sectoral credit

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:

$$C_{kit} = \frac{L_{kit}}{\sum_{j\neq k} L_{it}} \quad [4]$$

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

[14] Our monthly data allows us exploit richer information sets from higher data frequency relative to annual data sets. High frequency data sets can improve our understanding of monetary policy issues (Bernanke and Boivin, 2003). They are more appropriate for capturing volatile market conditions, which might be disguised by other dominating effects or obscured by relatively low-frequency data (Engle, 2004). For instance, structural shocks to the real oil prices often exhibit delayed reactions that are better assessed at monthly frequency (Kilian, 2009).

[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 14 countries for which we could gather reliable data.

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

[17] Although we use banking sector-wide flow of credit to industries from statutory central bank credit registers, we considered bank-level allocation. However, we note the challenge that data on bank sectoral exposures are not directly available from commercial databases. Even when we considered bank-level sectoral 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, data is mainly available 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 oil 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. Nevertheless, we gain some bank-level evidence using a restricted database of the Kazakh banks.

$\sum_{j \neq k} L_{it}$ 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 on the 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.

5.2.2. Defining and verifying the strength of oil price booms

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 (see Plante and Dhaliwal, 2017) 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 boom using the conceptual idea that it refers to situations where actual market prices substantially exceed expected prices (see Plante and Dhaliwal, 2017).

Consequently, we derive our oil boom measure as the percent deviations between actual and forecast oil price in period *t*,

$$Boom_t = \begin{cases} 100 * \dfrac{(Actual_t - Forecast_t)}{Actual_t}, \text{during time } t \\ 0, \qquad \text{otherwise} \end{cases} \qquad [5]$$

We use real spot prices as a proxy for actual prices, while the forecast prices are represented by real oil future contract data. Both price series are obtained from the EIA database[18]. The rationale for using futures prices (as a measure of oil price forecasts) is that they embody market operators' best views and expectations about prices[19]. An added advantage of this approach is that these *market expectations* are accessible or observable by all oil producing countries.

A second issue which we address is heterogeneity in terms of 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 equation [5] using country-specific weights as follows,

$$w_i = \frac{EV_b^{oil}}{EV_b^{Tot}} \qquad [6]$$

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[20]. These country weights are sensible because the

[18] These oil price series are deflated using Consumer Price Index (CPI) data and normalised to (2012=100).
[19] 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 in this study where we use monthly data.
[20] We use 2012 as our base year.

implication, size or 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 equation [5]; (ii) embodies country-specific conditions via equation [6]; and (iii) mitigates the endogeneity concerns arising from unpredictability and country-induced supply side shocks.[21] 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 as part of our robustness tests.

5.2.3. Strength of commodity price boom

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

$$\ln P_{c,t} = \alpha_{c,0} + \alpha_{c,1} t + \alpha_{c,2} t^2 + \sum_{p}^{3} \theta_{c,p} \ln P_{c,t-p} + \varepsilon_{c,t} \qquad [7]$$

The oil price shocks are then measured as the residuals of the regression above. Gven that commodity prices can be I(1) or I(2), this shock has the added advantage that it makes the shock measure stationary, and it 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.

[21] For instance, new oil discoveries or geopolitical events.

Finally, in order to test the robustness of the boom measure, we regress the boom variable (from equations 5 and 6) on the positive oil shock variable (retrieved from equation 7) using robust standard errors. As shown in equation [8] 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 to capture consistent or persistent upswings in oil prices:

$$Boom_{it} = 0.79\ (5.73) + 1.94\ (4.49) * positive\_shock_{it} \qquad [8]$$

$$R^2 = 0.45$$

5.3. *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 level of sectoral output, total deposits, equity capital, interest rate, exchange rate, liquidity, size of the banking sector, institutional quality[22] and an OPEC dummy[23]. Due to the monthly frequency of our data, we could not obtain data for some usual control variables, e.g. investments, GDP, trade openness, population density, corruption and democracy scores. Information on these variables are mainly available in annual frequency. However, we believe that some of the variables employed in our regressions capture dimensions and dynamics in these excluded variables such that the omitted variable problems are mitigated. For instance, we expect the sectoral output indices to mirror the level of investment and GDP across our sample; while our composite institutional quality variable should also capture the state of corruption and democracy in these countries.

[22] See Appendix C for details on the construction of our institutional quality measure using principal component analysis (PCA).
[23] See Appendix A for detailed definitions and sources of the variables used in this study.

5.4. 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 service sector. Although left-skewed, the standard deviations for both variables suggest considerable cross-country variation in the level of sectoral bank credit allocation. In particular, it is noteworthy to highlight that, on average, service 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.

[INSERT TABLE 2 HERE]

6. Empirical results

6.1. 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. The results 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.

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

Next, we focus on the endogeneity of the boom measure using the Durbin-Wu-Hausman (DWH) procedure, which allows us test for the corresponding orthogonality condition under the null hypothesis that the boom measure can be treated as exogenous within our model[24]. 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 15.27 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. This test result therefore justifies an IV estimation approach. Hence in our baseline results given in Table 3, we present both OLS and IV estimations for the sectoral bank credit allocation models.

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. First, because we include fixed effects in the model, the instrument ought to have time and cross-sectional variations. Second, the instruments 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 easily verifiable, given that all our 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

[24] We consider the plausible case in which other RHS variables might be endogenous. Following from a battery of Durbin-Wu-Hausman endogeneity tests on our RHS variables, we treat exchange rates as endogenous within our model estimations. The test results are available from the authors upon request.

second consideration, we resort to the strong statistical significance of the instruments in the first-stage IV regressions[25], 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.

[INSERT TABLE 3 HERE]

It is noted 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[26]. In particular, the Hansen *J* test results are supported by a visual inspection of the IV and OLS estimates in Table 3, corroborating the importance of controlling for 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.

With respect 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 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 or allocation are

[25] See Table B2 in Appendix B.
[26] The Kleibergen and Paap (2006) underidentification and weak identification LM test statistics also reject the null hypotheses that the IV models are underidentified or weakly identified

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. Hence, this credit allocation pattern is potentially a channel for the falling investment in manufacturing during commodity booms.

We now consider the effects of the control variables in our baseline regressions, namely sector output, interest rate, exchange rate, size of the banking sector, liquidity, equity capital and 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, it is to be noted 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 the service 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 service sector loan shares are increasing in banking system capitalization. However, the bank deposits coefficients suggest that banks offer more to the manufacturing sector than service 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.

6.3. Robustness tests: Quantile regression estimates

There may 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 by isolating the proportion of the sample which lies on or below the quantile regression line.

Table 4 presents the coefficient estimates of the quantile regressions across 0.1-0.9 quantiles. It is to be noted 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. 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 service 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 most 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.

[INSERT TABLE 4 HERE]

[INSERT TABLE 5 HERE]

6.4. *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)[27]. 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

$$op_t^+ = \max(0, \Delta op_t) \quad [9]$$

To construct the positive NOP variable that measures oil price increases, Hamilton then suggested a comparison of oil prices with where they had been over the previous year, rather than where they were the previous month, so that the NOP is the increase from the previous year's monthly high price if it is positive, but zero otherwise:

$$nop_t = \max[0, op_t - \max(op_{t-1}, op_{t-2}, \ldots, op_{t-12})] \quad [10]$$

[27] See Bjørnland (2009) and Wang, et al. (2013) for applications in financial market research.

Using this measure, we then derive country-specific equivalents using the weights in equation. [6]. Our alternative boom measure can thus be specified as

$$Boom_{it}^{2} = nop_t \times w_i \qquad [11]$$

We employ a third, yet intuitive measure of oil boom that is based on break even oil prices (BEP). The external breakeven oil price is the oil price at which an oil-rich country's current account balance is zero. This measure is superior to the alternative fiscal breakeven price (the oil price that is needed for an oil exporting country to balance its budget in time *t*), which suffers from serious limitations, despite its 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[28]. 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 as 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 (BEP) is calculated by subtracting a country's current account balance CA_{it} ($) from the value

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

of its net oil exports revenue EV_b^{oil} ($) and dividing this measure by the volume of net oil exports (barrels):

$$BEP_{it} = \frac{EV_{it}^{oil} - CA_{it}}{Q_{it}^{oil}} \quad [12]$$

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

$$Boom_{it}^{3} = [0, (op_t - BEP_{it}) * w_i] \quad [13]$$

The regression results for the two alternative boom measures are presented in Table 6. In Table 6, the model estimations indicate that credit contraction (expansion) to the manufacturing (service) 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.

[INSERT TABLE 6 HERE]

6.5.Additional robustness checks

There might be three outstanding but valid criticisms of our analyses so far. First, using the manufacturing sector as the tradable sector of oil producers might be inappropriate since the manufacturing sectors across these economies are weak, and may therefore face greater credit constraints[29]. Secondly, due to the above limitation, it might be argued that manufacturing firms in oil producing countries hardly rely on external finance. Thirdly, the challenge with any analysis relying on aggregated data is the difficulty to discern or disentangle firm-level behavior from unobserved aggregate shocks, such that changes in the outcome variables might

[29] See Beck, *et al*. (2005) and Yuxiang and Chen (2011)

be confounded with unobserved attributes of banks. To address these issues, we undertake three additional tests in the following sub-sections.

6.5.1. Alternative tradeable sector

Firstly, 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 cost of oil production and number of oil rigs as instruments to identify the effects of oil price booms on agricultural loan share. Intuitively, agricultural performance (and by extension its credit prospects) may 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.[30] Our underlying finding that credit allocated to the tradeable sector contracts during oil booms remains intact. Hence our findings are robust to alternative tradeable sector specification or definition.

[INSERT TABLE 7 HERE]

6.5.2. Firm external finance dependence

Secondly, we explore the potential criticism about the credit reliance of manufacturing sectors across sampled countries by investigating the level of loan dependence across a panel of manufacturing firms. We collect firm-level data[31]on manufacturing enterprises from the World

[30] In this case the orthogonality conditions will be violated.
[31] See Appendix A for a full list of variables and definitions.

Bank Enterprise Survey (WBES)[32]. Following Rajan and Zingales (1998) and Cetorelli and Gambera (2001), we measure firm external finance dependence as,

$$Dep_{it} = \frac{Loan_{it}}{Cost_{it}} \qquad [14]$$

where $Loan_{it}$ is the total value of bank loan secured by firm *i* during period *t* while $Cost_{it}$ is the firm's production cost. 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 firm 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 measure across the board, indicating that the distribution of the loan dependence variable is right-skewed. This remains unchanged when we evaluate these statistics at the country-level. The last column of Table 8 contains information on the proportion of firms with disbursed bank loans during the study period. Across the whole sample of 1415 manufacturing firms, 637 firms (45% of sample) had bank loans during the period under consideration; indicating that around half of our sample relied on external finance. The proportion of firms relying on bank loans appears significant across sampled countries, indicating 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.

[INSERT TABLE 8 HERE]

6.5.3. A closer look at bank behavior: A microeconomic case study of Kazakh banking industry

So far, we find a strong association between oil booms and bank credit allocation pattern for the period 1994-2017. However, as we stated previously, a micro-econometric approach allows

[32] 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 spanning 7 of the sampled countries, as countries not covered by the WBES are unavoidably omitted from the sample.

us to disentangle bank-level credit allocation behavior from other macro effects. This also mitigates concerns about changes in the outcome variables being confounded with unobserved attributes of banks. Thanks to having a panel dataset constructed using confidential monthly data covering all banks in Kazakhstan[33] over the period 2008-2017, we can undertake a microeconometric evaluation of bank-level sectoral credit allocation. We re-estimate Equation [3] using analogous bank-level dependent variables (loan shares), but we are unable to control for other bank level controls[34]. Table 9 contains the results of the bank-level regressions. In general, the model coefficients are consistent in terms of their signs, although some of the estimates lose statistical significance. The results indicate that the relationship between the three alternative boom measures and sectoral credit patterns is consistent with our previous findings: during oil booms, manufacturing (services) sector share of credit expand (contracted).

[INSERT TABLE 9 HERE]

6.6.Further estimation issues

Although we employ an IV approach, we nonetheless consider the plausibility that our IV estimator might not fully alleviate the endogeneity of the boom measure. This problem is largely consistent with the reality that our data sample contains the two largest oil-dependent countries namely Saudi Arabia and Russia[35]. Hence, we conduct one final sensitivity test by re-estimating our baseline model with a data sample that excludes Saudi Arabia and Russia.

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[33] We contacted several central banks to obtain bank-level data, but the National Bank of Kazakhstan was the only source with a favourable response..

[34] “According to p.2 Article 8 of the Law of the Republic of Kazakhstan “On State Statistics” from March 19th, 2010 №257-IV (further – the Law), using of primary statistical data on sectoral loan exposure in breakdown by respondents (in respect of one specific respondent) is prohibited. Also, in accordance with p.5 Article 8 of the Law, statistical information and databases that allow the respondent to be identified directly or indirectly or to determine the primary statistical data about him, are confidential and cannot be disseminated without the respondent's consent”: National Bank of Kazakhstan, February 2018. Accordingly, we were only granted anonymised monthly sectoral loan shares data across the different 32 banks, making it impossible to match the credit information to potentially publicly available data on bank-level characteristics. Hence, we are only able to control for sector-level factors such as sectoral output, exchange rate and average interest rate.

[35] Production numbers from the British Petroleum (BP)’s 2017 statistical bulletin revealed that both countries have historically accounted for around 26% of global oil production.

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 (service) sector share of bank credit.

[INSERT TABLE 10 HERE]

7. 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 banks 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 issue 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 14 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 (service) 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 tradable sector investments and productivity performance.[36] This pattern is also consistent with the view of a financial resource curse (Beck, 2011; Benigno and Fornato, 2014). These findings are robust to a battery of robustness checks such as an instrumental

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

variables approach which caters to heterogeneity and endogeneity concerns; alternative measures of oil boom, quantile regressions aimed at isolating our relationship of interest at different points in the conditional distribution of credit allocation, an alternative definition of the tradable sector, microeconometric evaluation, as well as running regressions that exclude large oil producers.

Our results have important policy implications. First it should be clear that the strong rejection of our null hypothesis indicates that central banks across our sample 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 to mitigate the misallocation of resources during an episode of financial resource curse.[37] This idea seems justified since our results indicate that the observed capital allocation across the sampled countries might be well short of the *"public good"* function of the financial system.

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 further investigate micro-level bank lending behaviour during commodity booms. With such microdata it would be

[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.

interesting to unravel the channels through which commodity booms shape bank credit policies in the context of (i) foreign currency exposure (ii) market power and (iii) management quality. However, we are aware of the difficulty stemming from the lack of suitable microdata on sectoral lending spanning a reasonably long period[38], required to conduct a meaningful analysis of commodity price shocks.

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

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 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)
Manufacturing production index	Production volume index (2012=100)	Thomson Datastream
Services output index	Index of services sector output (2012=100)	Thomson Datastream
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
WBES Firm-level data		
Cost	Total operating cost	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	-11.733*	0.000	-11.571*	0.000
Manufacturing	-5.324*	0.000	-5.196*	0.000
Services	-5.395*	0.000	-4.835*	0.000
Exchange rate	0.234	0.408	-0.966	0.167
Interest rate	-5.713*	0.000	-8.674*	0.000
Deposit	-5.782*	0.000	-3.916*	0.000
Capital	-4.029*	0.000	-4.393*	0.000
Liquidity	-5.386 *	0.000	-3.931*	0.000
Size	-2.295*	0.011	-3.897*	0.004
Institutional quality	-2.481*	0.007	-2.588*	0.005
Manufacturing index	-12.565	0.000	-13.330*	0.000
Services index	-6.999*	0.000	-5.791*	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 boom and instruments

	1	2	3
Temperature	4.439***		
	[0.675]		
Oil rigs		0.001***	
		[0.000]	
Variable cost			0.034***
			[0.004]
Constant	-0.049***	-0.093***	-0.120***
	[0.007]	[0.013]	[0.015]
R-sqr	0.43	0.44	0.45
N	2310	2310	2310

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. 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. 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 (Table C1).

Table C1: Principal Component Analysis (PCA)

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	4.28	3.27	0.71	0.71
Comp2	1.01	0.62	0.17	0.88
Comp3	0.39	0.22	0.07	0.95
Comp4	0.17	0.09	0.03	0.97
Comp5	0.08	0.01	0.01	0.99
Comp6	0.07	-	0.01	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 the quality of economic or political institutions is likely to embody some degree of persistence: i.e. changes are gradual or slow-changing (North, 1994; Acemoglu and Robinson, 2010).

Appendix D

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

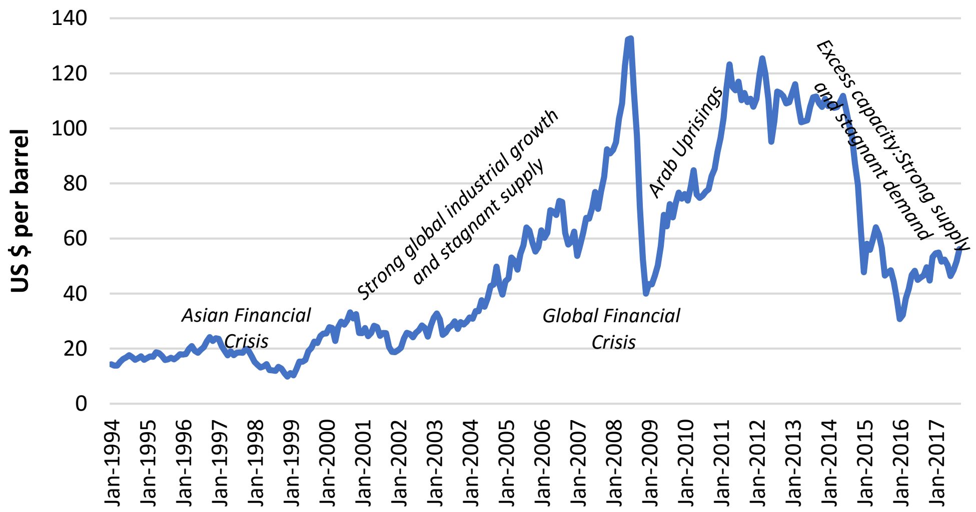

Figure D2: Manufacturing sector share of loans versus oil boom

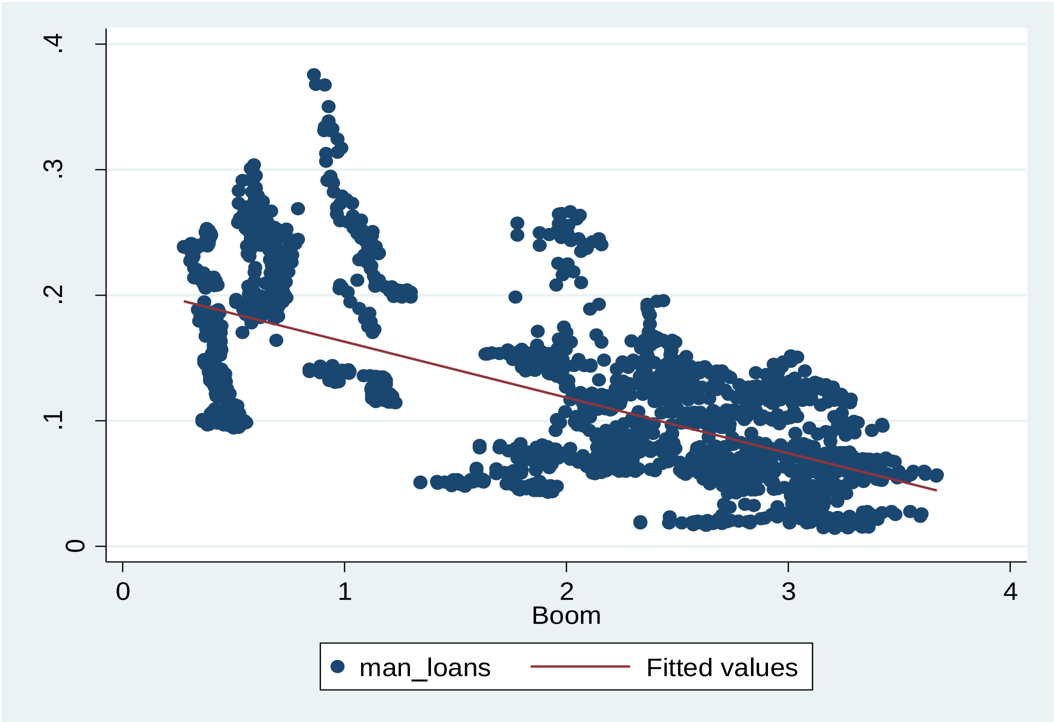

Figure D3: Service sector share of loans versus oil boom

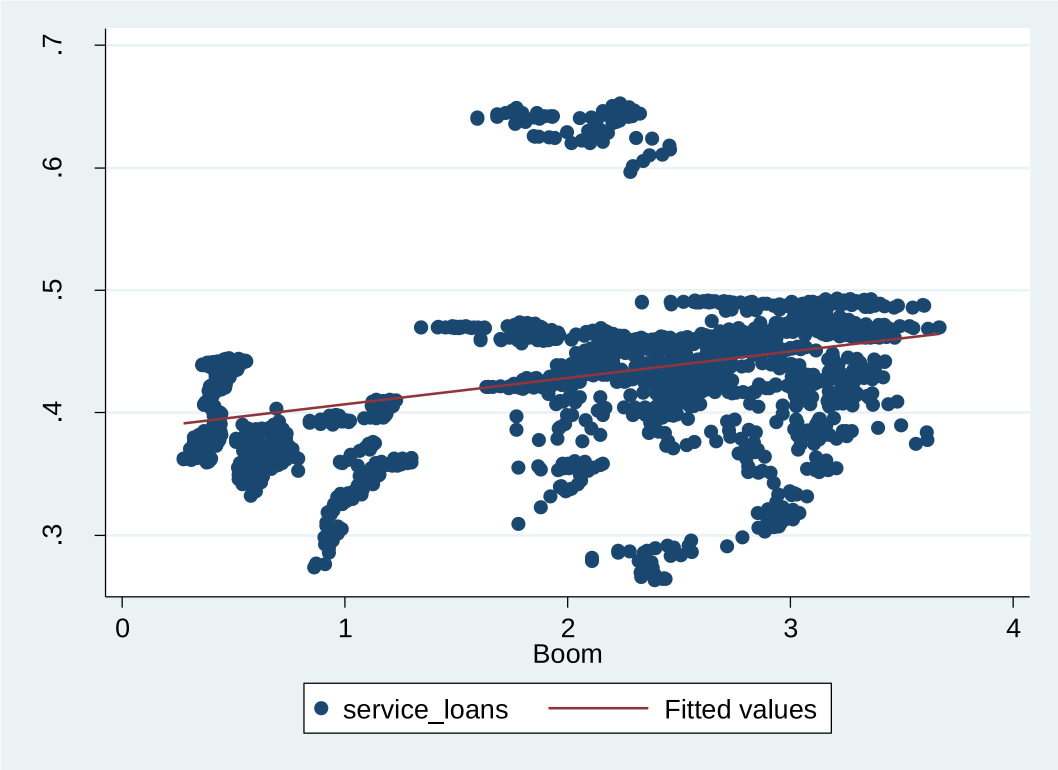

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Table 1:Income, oil contribution and financial development across countries, 2016.

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
Norway	63810.8	0.03	53.00	145.0
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)

Table 2:Summary Statistics for the variables used in the study

Variable	Mean	Std. Dev.	Min	Max	# of countries	# of obs.
Banking sector-level data						
Agriculture share of credit (%)	1.98	1.83	0.001	8.73	14	2310
Manufacturing sector share of credit (%)	12.21	6.87	1.41	37.58	14	2310
Service sector share of credit (%)	42.67	6.51	26.35	65.26	14	2310
Oil price boom (%)	0.48	1.17	0.001	14.39	14	2310
Real interest rate (%)	9.81	7.16	-3.44	47.54	14	2310
Total deposits (billion, ppp $)	17.90	64.80	0.03	550	14	2310
Total capital (billion, ppp $)	0.87	2.56	-0.02	20.40	14	2310
Real exchange rate (index, 2012=100)	110.53	38.65	62.52	395.12	14	2310
M2/Reserve	3.42	1.86	0.44	22.53	14	2310
Total assets (billion, ppp $)	6.22	12.90	0.04	83.70	14	2310
OPEC (Dummy=1, 0 otherwise)	0.42	0.49	0	1	14	2310
Institutional quality	0.32	0.93	-1.68	2.01	14	2310
Manufacturing index	93.32	13.67	51.08	130.05	14	2310
Services index	92.78	23.04	20.62	195.66	14	2310
Instrumental variables						
Real unit labour cost of per barrel of oil in the US ($, 2012=100)	100.58	7.78	67.48	117.84	14	2310
Average global temperature (degree Celsius)	0.53	0.17	0.10	1.11	14	2310
Total world oil rigs	2704.42	714.92	1156	3900	14	2310

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

	Manufacturing loan share		Services loan share	
Variable	OLS	IV	OLS	IV
Boom	-0.001*	-0.011***	0.001**	0.008***
	[0.000]	[0.003]	[0.000]	[0.002]
Deposit	0.012	0.012***	-0.007	-0.006*
	[0.014]	[0.004]	[0.014]	[0.003]
Capital	0.002	0.004***	0.005*	0.004***
	[0.004]	[0.001]	[0.003]	[0.001]
Interest rate	0.152***	0.129***	-0.087*	-0.074***
	[0.042]	[0.017]	[0.047]	[0.022]
Exchange rate	-0.006	-0.012**	-0.004	-0.0001
	[0.027]	[0.006]	[0.020]	[0.004]
Liquidity	-0.012***	-0.011***	0.006	0.005***
	[0.004]	[0.001]	[0.004]	[0.001]
Size	-0.010**	-0.010***	0.004	0.004***
	[0.005]	[0.001]	[0.005]	[0.001]
OPEC	0.096***	0.093***	-0.052***	-0.049***
	[0.009]	[0.006]	[0.007]	[0.003]
Institutions	0.004	0.004***	-0.006	-0.006***
	[0.005]	[0.001]	[0.004]	[0.001]
Sector output index	0.001	0.003	0.007	0.003
	[0.018]	[0.005]	[0.010]	[0.005]
(Centered) R^2	0.61	0.53	0.48	0.40
Month dummies	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
Country dummies	Yes	Yes	Yes	Yes
Under id test: KP LM statistic		35.01		33.79
Weak id test: KP LM statistic		25.48		24.87
Over id test: Hansen J statistic		0.03		0.04
Hansen *J*-test (p-value)		[0.86]		[0.84]
Excluded Instrument		Weather		Weather
N	2310	2310	2310	2310

Notes: The dependent variables are the sector shares of total credit, defined as the ratio of manufacturing or services sector loans to total loans. The IV specifications use temperature, one and two lags, as well as lagged exchange rate. Kleibergen-Paap weak and underidentification LM and Wald tests are conducted under the null hypotheses that model is weakly identified and underidentified, respectively. 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.

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]
Sectoral output index	0.0492***	0.0571***	0.0445***	0.0025*	0.0027**	0.0012	0.0012	-0.0042	-0.0057
	[0.0059]	[0.0077]	[0.0098]	[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	2310	2310	2310	2310	2310	2310	2310	2310	2310

Notes: 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]
Sectoral output index	-0.0633***	-0.0647***	-0.0538***	-0.0486***	-0.0334***	-0.0250***	-0.0241**	-0.0274	-0.0521***
	[0.0119]	[0.0050]	[0.0038]	[0.0064]	[0.0062]	[0.0057]	[0.0083]	[0.0146]	[0.0127]
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	2310	2310	2310	2310	2310	2310	2310	2310	2310

Notes: 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

Table 6:Robustness test: Alternative boom measures.

	Manufacturing loan share		Services loan share	
	Hamilton	Break-even	Hamilton	Break-even
Boom	-0.1318***	-0.0512***	0.0896***	0.0365***
	[0.0349]	[0.0120]	[0.0228]	[0.0081]
Deposit	0.0056	0.0091***	-0.0010	-0.0039
	[0.0037]	[0.0033]	[0.0034]	[0.0032]
Capital	0.0021**	-0.0018	0.0052***	0.0081***
	[0.0010]	[0.0014]	[0.0009]	[0.0012]
Interest rate	0.1534***	0.1710***	-0.0806***	-0.1010***
	[0.0165]	[0.0194]	[0.0219]	[0.0256]
Exchange rate	-0.0172***	-0.0218***	0.0032	0.0065
	[0.0061]	[0.0064]	[0.0048]	[0.0050]
Liquidity	-0.0127***	-0.0168***	0.0069***	0.0095***
	[0.0012]	[0.0016]	[0.0011]	[0.0013]
Size	-0.0109***	-0.0105***	0.0043***	0.0039***
	[0.0013]	[0.0012]	[0.0011]	[0.0011]
OPEC	0.0894***	0.0937***	-0.0478***	-0.0503***
	[0.0057]	[0.0054]	[0.0033]	[0.0031]
Institutions	0.0041***	0.0041***	-0.0063***	-0.0065***
	[0.0008]	[0.0007]	[0.0006]	[0.0006]
Sector output	0.0038	0.0049	0.0116**	0.0053
	[0.0053]	[0.0052]	[0.0053]	[0.0055]
(Centered) R^2	0.56	0.57	0.41	0.44
Month dummies	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
Country dummies	Yes	Yes	Yes	Yes
Under id test: KP LM statistic	71.88	113.86	77.71	113.63
Weak id test: KP LM statistic	29.50	58.32	32.90	58.56
Over id test: Hansen J statistic	0.01	0.14	0.01	0.19
Hansen *J*-test (p-value)	[0.93]	[0.71]	[0.90]	[0.66]
Excluded Instrument	Weather	Weather	Weather	Weather
N	2282	2282	2282	2282

Table 7:Robustness test: IV Alternative tradeable sector.

	FE-IV
Boom	-0.0133**
	[0.0060]
Deposit	0.0074***
	[0.0028]
Capital	-0.0010
	[0.0013]
Interest rate	0.0340*
	[0.0191]
Exchange rate	-0.0028
	[0.0035]
Liquidity	0.0008
	[0.0014]
Size	-0.0026**
	[0.0012]
OPEC	0.0038**
	[0.0018]
Institutions	0.00002
	[0.0004]
Sector index	-0.0090***
	[0.0015]
(Centered) R^2	0.36
Month dummies	Yes
Year dummies	Yes
Country dummies	Yes
Under id test: KP LM statistic	9.12
Weak id test: KP LM statistic	13.34
Over id test: Hansen J statistic	0.68
Hansen *J*-test (p-value)	[0.41]
Instrument	Oil rig & cost
N	2296

Notes: This table reports IV robustness tests of oil price boom and credit using an alternative tradeable sector- agricultural sector. The independent variables are analogous to those in Table 3, 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 lagged values of variable cost of oil production and global oil rig counts as instruments. Kleibergen-Paap weak and underidentification LM and Wald tests are conducted under the null hypotheses that model is weakly identified and underidentified. 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.

Table 8:Bank loan dependence in some oil-rich countries

Sample	Mean	Std. Dev.	# of firms	% with loans
Whole sample	**0.06**	**0.20**	**1415**	**46%**
Azerbaijan	0.03	0.11	88	24%
Brazil	0.10	0.18	452	78%
Nigeria	0.04	0.18	60	27%
Indonesia	0.04	0.17	406	51%
Kazakhstan	0.08	0.31	81	25%
Mexico	0.07	0.19	189	58%
Russia	0.09	0.25	103	52%

Notes: This table reports the loan dependence across some of the countries in our data sample. Source: World Bank Enterprise Surveys

Table 9:Sectoral loan allocation in the Kazakh banking industry

	Manufacturing			Agriculture			Service		
	Spot-forecast	Hamilton	Break-even	Spot-forecast	Hamilton	Break-even	Spot-forecast	Hamilton	Break-even
Boom	-0.013	-0.604***	-0.621***	-0.032	-0.398*	-0.374	0.010	0.505***	0.502***
	[0.040]	[0.158]	[0.130]	[0.026]	[0.241]	[0.283]	[0.025]	[0.140]	[0.177]
Interest	-0.023	-0.012	-0.037	0.282	0.312	0.295	-0.145	-0.163	-0.143
	[0.374	[0.381]	[0.382]	[0.396]	[0.409]	[0.403]	[0.267]	[0.275]	[0.272]
Exchange rate	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	[0.000	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Sector output	0.038	0.035	0.041	-0.022	-0.017	-0.017	-0.004	-0.009	-0.010
	[0.063	[0.063]	[0.063]	[0.040]	[0.043]	[0.043]	[0.017]	[0.018]	[0.018]
Constant	-0.290	-0.249	-0.306	0.125	0.094	0.098	0.461	0.484	0.488
	[0.623	[0.621]	[0.623]	[0.230]	[0.246]	[0.245]	[0.083]	[0.089]	[0.087]
Observations	3240	3240	3240	3240	3240	3240	3240	3240	3240
R-sqrd	0.030	0.032	0.031	0.029	0.030	0.029	0.016	0.020	0.018
Banks	34	34	34	34	34	34	34	34	34

This table reports OLS regressions on the relationship between alternative oil price boom measures and sectoral credit shares. Heteroskedasticity-robust standard errors reported in parenthesis are clustered for countries. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels respectively.

Table 10:Sectoral credit allocation regressions excluding Russia and Saudi Arabia

	Manufacturing	Agriculture	Services
Boom	-0.0093***	-0.0106***	0.0069***
	[0.0024]	[0.0036]	[0.0019]
Deposit	-0.0024	0.0091***	0.0076**
	[0.0037]	[0.0025]	[0.0033]
Capital	0.0007	-0.0017**	0.0048***
	[0.0012]	[0.0008]	[0.0010]
Interest rate	0.1114***	0.0417**	-0.0510***
	[0.0131]	[0.0168]	[0.0183]
Exchange rate	-0.0138***	-0.0027	-0.0153***
	[0.0049]	[0.0026]	[0.0039]
Liquidity	-0.0112***	-0.0018	-0.0026
	[0.0018]	[0.0012]	[0.0017]
Size	-0.0088***	-0.0028***	0.0010
	[0.0012]	[0.0010]	[0.0010]
OPEC	0.0878***	0.0048***	-0.0468***
	[0.0050]	[0.0015]	[0.0029]
Institutions	-0.0009	0.0007*	-0.0045***
	[0.0007]	[0.0004]	[0.0007]
Sector index	0.0022	-0.0102***	0.0108**
	[0.0051]	[0.0015]	[0.0053]
(Centered) R^2	0.65	0.48	0.34
Month dummies	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes
Country dummies	Yes	Yes	Yes
Under id test: KP LM statistic	35.43	34.17	13.51
Weak id test: KP LM statistic	27.59	26.39	10.44
Over id test: Hansen *J* statistic	0.043	2.29	0.16
Hansen *J*-test (p-value)	[0.98]	[0.98]	[0.69]
Instrument	Weather	Oil cost and rig	Weather
N	1930	1930	1930

This table reports robustness tests of oil price boom and credit using a parsimonious data sample which excludes Russia and Saudi Arabia. The dependent variables are analogous to those in Tables 3-7. Kleibergen-Paap weak and underidentification LM and Wald tests are conducted under the null hypotheses that model is weakly identified and underidentified. 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.