

Oil booms, bank productivity and natural resource curse in finance

Morakinyo O. Adetutu^{a,*}, Kayode A. Odusanya^a, John E. Ebireri^a, Victor
Murinde^b

^a*Nottingham Trent University, Shakespeare Street, Nottingham, NG1 4FQ, UK*

^b*Centre for Global Finance, SOAS University of London, Thornhaugh Street, London,
WC1H 0XG, UK*

Abstract

Using a rich monthly microdata, this study is the first one to investigate the effect of commodity booms on bank productivity in the context of resource-endowed economies. Consistent with the axiom of a natural resource curse in finance, we find significant decline in banks' total factor productivity (TFP) during episodes of oil booms.

Keywords: Banks; resource curse; oil boom; total factor productivity (TFP)

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*Corresponding author

Email address: morakinyo.adetutu@ntu.ac.uk (Morakinyo O. Adetutu)

1. Introduction

An emerging idea in the finance literature¹ is that the low levels of financial development in commodity-based economies is a consequence of their natural resource abundance.² A few earlier works (Beck, 2011; Bhattacharyya and Hodler, 2014) provide some indication of a natural resource curse in financial sectors of resource-rich economies, based on the macro-level relationship between financial development indicators (e.g. private credit to GDP ratio) and resource dependence (e.g. commodity rents). However, there are concerns about (i) the challenge of disentangling the impact of resource dependence on the financial system from those of other aggregates, and (ii) the likely endogeneity of resource dependence measures (Beck and Poelhekke, 2017). Even when microeconomic evaluations on the impact of resource dependence on bank-level performance indicators have attempted to address the above concerns, the results are inconclusive (Beck, 2011; Beck and Poelhekke, 2017)³. This is potentially due to two issues.

First, the microeconomic studies are based on a range of bank performance measures which do not provide compelling empirical evidence. For instance, Beck (2011) used different indicators on bank business strategy, cost-income ratios and bank stability, while Beck and Poelhekke (2017) employed deposit and loan measures. Across both studies, the impact of resource dependence on bank-level performance is either statistically insignificant or contradictory across indicators. Second, the studies rely on annual data, which may not adequately capture commodity market dynamics. Commodity markets are notoriously volatile and their effects on financial markets can be short-lived, hence higher frequency data might be crucial in capturing these dynamics (Faust et al., 2004; Ferraro et al., 2015).

¹See Beck (2016) for a review.

²A large literature explains the poor economic performance of resource-dependent countries under the Dutch disease phenomenon (Corden and Neary, 1982), which refers to the adverse effect of natural resource booms on the tradable sector.

³To our knowledge, only these two papers fall into this category.

Thus, this letter employs total factor productivity (TFP) as a measure of bank performance. We believe that TFP offers a more comprehensive and robust measure of firm-level performance. Further, we use a rich monthly micro dataset on the Kazakh banking sector, which allows us to more precisely account for oil market volatility. The Kazakh banking sector offers an interesting case study on financial natural resource curse. It is a major oil producer that accounts for 1.8% of global oil reserves (BP, 2017), with the oil sector contributing over 60% to total exports (World Bank, 2018). However, despite posting comparable growth credentials as the East Asian tigers, it has experienced its fair share of boom-related financial crises (IMF, 2001; Glass et al., 2014). Our research therefore contributes to the literature by being the first to provide concrete evidence on the potential impact of natural resources on bank-level productivity as an axiom of the natural resource curse.

2. Data

We construct a database on banking and oil price variables from January 2008 to October 2017 using information from the National Bank of Kazakhstan (NBK) and the Energy Information Administration (EIA). The banking data combines publicly-available and restricted-use information on bank financials, obtained from the Research Department of the NBK.

2.1. Bank-level TFP

Total factor productivity (TFP) is derived from the production function specification:

$$y_{it} = \alpha + \beta_1 k_{it} + \beta_2 l_{it} + \beta_3 m_{it} + \omega_{it} + \varepsilon_{it} \quad (1)$$

where y_{it} is the log of output of bank i in period t , represented by the sum of loans and investment securities. k_{it} is the log of the state input (capital), given by fixed assets; l_{it} is the log of free/variable input (labour), represented by wages. m_{it} is the log of intermediate input which we proxy with total deposits.

ω_{it} is the unobservable productivity and ε_{it} captures white noise. We assume that ω_{it} evolves following a first-order Markov process:

$$\omega_{it} = E(\omega_{it}|\omega_{it-1}) + u_{it} \quad (2)$$

where u_{it} is a random component. We compute ω_{it} following the procedure proposed by Akerberg et al. (2015), which overcomes the simultaneity bias that could arise from the potential correlation between the banks observable inputs and ω_{it} . Under this procedure, we use the inverse demand function for the proxy variable, along with other model parameters, to obtain the residuals ω_{it} .

2.2. Defining oil boom

Our main independent variable captures episodes of oil price booms in any period t : $boom_t$, which we derive as an indicator variable that assumes the value of 1 if actual oil prices exceed expected prices, and zero otherwise. We use real monthly spot prices and real oil futures as proxies for actual and expected prices, respectively. The rationale for using oil futures as a measure of market expectations is that they embody market operators best views or rational expectations about future spot prices (Wu and McCallum, 2005; Hamilton, 2009).

By employing an oil price boom variable, we bypass the endogeneity problems in traditional resource rent measures by parsing out (and using) the exogenous international oil price component from the endogenous resource extraction-induced component. This approach seems justified in the Kazakhstan context as we find the exogenous oil price swings over the study period to be the main driver of oil rents in the face of stable oil production (see Fig. A1 in the online appendix). Table 1 contains the summary statistics of our key variables. See online appendix for a detailed description of all variables in this paper.

Table 1: Descriptive statistics

Variable	Obs.	Mean	Std Dev.	Min.	Max.
TFP (logs)	2357	16.680	1.830	9.268	19.826
Boom (dummy)	118	0.421	0.494	0	1

3. Econometric framework

To gauge the relationship between bank productivity and oil booms, we fit the following model:

$$TFP_{it} = \alpha_i + \alpha_t + \beta_it + \delta_1 boom_t + \delta_2 X_{it-2} + \delta_3 activity_{t-2} + v_{it} \quad (3)$$

where TFP_{it} is bank-level total factor productivity, the bank dummies α_i capture any time-invariant characteristics that may influence bank performance; α_t are time dummies that control for the impact of monetary policy, economic, political events etc., occurring at the national and global level; β_it are bank-specific trends to capture the slow-moving effects of technological progress, human capital development, etc., which may evolve at different rates across banks. $boom_t$ is the oil boom variable defined in section 2.2. To ensure that δ_1 captures the impact of the boom, rather than other contemporaneous characteristics, we include X_{it-2} , a vector of bank-level characteristics such as age, size and ownership. These controls are lagged $t - 2$ to mitigate any potential endogeneity problems. We also capture the level of economic activity using the monthly investment activity index, $activity_{t-2}$. v_{it} is an idiosyncratic error term.

4. Empirical results

Table 2 reports the results of the TFP regressions. In column 1, we regress TFP on the oil boom variable without any control variables. We find a strong negative effect of oil booms on bank TFP, which indicates that during oil booms, bank-level TFP declined by 79% on average. This effect is significant at the 1%

level. In column 2, we add bank-level characteristics and the economic activity variable. The estimated boom coefficient drops in magnitude but remains statistically significant at 1%. The impact of bank age on TFP is negative and significant at the 10%-level, while bigger and foreign owned banks are found to have higher levels of productivity, albeit the latter is not statistically significant at conventional levels. In column 3, we go beyond establishing the effect of oil boom on bank performance by further exploring whether bank performance during commodity booms is an axiom of the natural resource curse in finance.

Table 2: Baseline results

Dep var.: TFP	1	2	3
$boom_t$	-0.797*** [0.158]	-0.597*** [0.108]	-0.383*** [0.126]
$size_{it-2}$		0.448*** [0.043]	0.475*** [0.041]
age_{it-2}		-1.529* [0.911]	-1.635* [0.913]
$foreign_{it-2}$		0.035 [0.049]	0.025 [0.048]
$activity_{it-2}$		0.559 [1.128]	0.617 [1.109]
$boom_t \times FCY_{it-2}$			-0.907*** [0.248]
R-squared	0.844	0.886	0.887
Wald/F-test	0.000	0.000	0.000
Bank FE	Yes	Yes	Yes
Period FE	Yes	Yes	Yes
Bank-specific trend	Yes	Yes	Yes
Observations	2357	2303	2303

Notes: OLS regressions. Robust standard errors in parenthesis. Clustering at the bank-level does not qualitatively affect results. **, *, & * indicate significance at 1, 5 & 10%-level, respectively.

In the seminal theoretical treatment of natural resource curse, adverse exchange rate effect is highlighted as an important channel through which commodity booms impact economic performance (Corden and Neary, 1982). Meanwhile, a related channel for the financial sector is that windfalls from abroad often lead to episodes of excessive foreign capital (Benigno and Fornaro, 2014).

Kazakh banks are particularly known to demonstrate a strong preference for foreign investments and assets during episodes of abundant foreign currency (IMF, 2005; Glass et al., 2014). Given the foregoing, we depict this foreign asset channel by adding to our specification an interaction term between the oil boom variable and foreign loan exposure: $boom_t \times FCY_{it-2}$, where FCY is the ratio of foreign currency lending to total lending.

Column 3 contains the results from the augmented regression. The coefficient on the boom variable remains statistically significant at 1%, indicating a 38% decline in TFP. The interaction coefficient is also negative and significant at 1%, suggesting that higher foreign currency exposure further decreases bank productivity during commodity booms. This finding seems consistent with the Dutch disease postulation on the detrimental effect of boom-related currency effects on economic performance. Moreover, it is well-documented that the excessive risks associated with increased foreign currency exposure during episodes of economic booms, have led to severe financial crises in the Kazakh banking sector (Glass et al., 2014).

4.1. Robustness checks

We conduct two robustness exercises. First, we check the sensitivity of our results to the TFP measurement by constructing an alternative TFP measure following the Levinsohn and Petrin (2003) procedure. We then re-estimate all the models in Table 2 using this alternative TFP measure. The results from these models, which are presented in Table 3, are qualitatively analogous to our baseline results and main conclusions. Second, because our panel is not strongly balanced⁴, there is potential for endogeneity of attrition (Hopenhayn, 1992; Farinas and Ruano, 2005). To this end, we further employ a TFP measure that accounts for firm attrition by treating productivity as a function of its past values and a survival indicator (Olley and Pakes, 1996; Rovigatti and Mollisi,

⁴Due to mergers and acquisitions, there is a non-random exit of a few banks from our sample. It is therefore conceivable that less productive banks exit the banking industry, leaving only the most productive banks in the sample.

2018). The results obtained from the attrition-corrected TFP measures are presented in Table 4. We find that attrition does not qualitatively affect our conclusion that bank productivity in the Kazakh banking sector is lower during oil booms.

Table 3: Re-estimations using Levinsohn and Petrin (2003) method

Dep var.: TFP	1	2	3
$boom_t$	-0.663*** [0.151]	-0.563*** [0.107]	-0.358*** [0.126]
$size_{it-2}$		0.362*** [0.042]	0.387*** [0.041]
age_{it-2}		-1.602* [0.909]	-1.703* [0.911]
$foreign_{it-2}$		0.036 [0.052]	0.026 [0.051]
$activity_{it-2}$		0.010 [0.010]	0.010 [0.010]
$boom_t \times FCY_{it-2}$			-0.864*** [0.251]
R-squared	0.851	0.863	0.865
Wald/F-test	0.000	0.000	0.000
Bank FE	Yes	Yes	Yes
Period FE	Yes	Yes	Yes
Bank-specific trend	Yes	Yes	Yes
Observations	2357	2303	2303

Notes: OLS regressions. Robust standard errors in parenthesis. Clustering at the bank-level does not qualitatively affect results. **, *, & * indicate significance at 1, 5 & 10%-level, respectively.

5. Conclusion

This note sheds new light on the existence of a natural resource curse in the financial sector of commodity-exporting economies. Using microeconomic data from the Kazakh banking sector, we find a significant decline in banks' TFP during episodes of oil booms and this negative impact is more pronounced for the banks with greater foreign currency exposure. Our results suggest that poor bank productivity during resource booms is an axiom of the natural resource curse.

Table 4: Re-estimations accounting for bank attrition

Dep var.: TFP	1	2	3
$boom_t$	-0.662*** [0.150]	-0.562*** [0.108]	-0.354*** [0.126]
$size_{it-2}$		0.363*** [0.042]	0.388*** [0.041]
age_{it-2}		-1.594* [0.909]	-1.694* [0.911]
$foreign_{it-2}$		0.035 [0.051]	0.026 [0.050]
$activity_{it-2}$		0.010 [0.010]	0.010 [0.010]
$boom_t \times FCY_{it-2}$			-0.865*** [0.250]
R-squared	0.850	0.866	0.867
Wald/F-test	0.000	0.000	0.000
Bank FE	Yes	Yes	Yes
Period FE	Yes	Yes	Yes
Bank-specific trend	Yes	Yes	Yes
Observations	2357	2303	2303

Notes: OLS regressions. Robust standard errors in parenthesis. Clustering at the bank-level does not qualitatively affect results. **, *, & * indicate significance at 1, 5 & 10%-level, respectively.

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