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Different behaviors in natural gas production between national and private oil companies: Economics-driven or environment-driven?

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ABSTRACT

This paper investigates firm-level efficiency in the petroleum industry during the period 2009–2015. A Jackknife model averaging method and two stochastic frontier models are utilized to estimate the input-output relation more accurately. The derived efficiency is then decomposed to predict the effect of various efficiency determinants with an emphasis on gas ratio and ownership. A significantly negative effect of natural gas ratio (in production portfolio) on efficiency is found for both National Oil Companies (NOCs) and privately-owned International Oil Companies (IOCs). This finding implies that the decline in natural gas ratio for IOCs is economics-driven, and the incline in gas ratio for NOCs is environment-driven. Therefore, the environmental objective is the NOCs' third non-commercial objective, alongside subsidizing below-market energy prices and offering excessive employment, as found in the literature. Governments may consider the transfer of subsidies from low energy prices to clean energy promotion, which leads to energy saving and emissions reduction.

1. Introduction

Given the severe pollution of coal and the slow growth of renewable energy, an abundant production of natural gas guarantees the supply of electricity under some requirements of emissions reduction, and hence balances the sustainable development of environment and economy. Therefore, coal and renewables are the competing sources of natural gas from a consumers' perspective. Many studies (Robinson et al., 2013; Simsek and Simsek, 2013; Wei et al., 2010) analyze the characteristics of these sources economically and environmentally. However, the major competitor to natural gas, from a producers' perspective, is crude oil, as petroleum enterprises decide the share of oil and gas in their production portfolio, which to some extent determines the supply of natural gas. Since natural gas produces fewer emissions than crude oil and coal, improving the share of gas production in petroleum industry benefits the environment from two perspectives. On the one hand, natural gas can be utilized to directly replace coal in electricity generation. On the other hand, gas is an alternative to oil in the transportation sector, which causes up to 40% CO_2 emission reductions (Hekkert et al., 2005).

Using data on 54 large petroleum firms, this paper finds that the average share of natural gas in portfolio decreased from 42.69% in 2009 to 40.96% in 2015, which implies that gas production might be less effective than oil production. In order to prove that such a decline in the gas ratio is economics-driven, the impact of natural gas share on firm-level efficiency needs to be estimated. In the little research that studies the efficiency of oil and gas firms, the focus is the difference between National Oil Companies (NOCs) and privately-owned International Oil Companies (IOCs) (i.e., the effect of ownership), and no one has studied the impact of natural gas ratio. Hartley and Medlock (2008) argue the major difference between IOCs and NOCs is that the IOCs focus on a commercial objective, while the NOCs have a wider range of non-commercial objectives due to political pressure. If the decline in gas ratio is economics-driven, as we expected, a sharper fall should be observed among IOCs, since they pay more attention to economic performance. This paper finds that the gas ratio decreased from 45.86% in 2009 to 42.18% in 2015 for IOCs, which further supports our hypothesis. However, an incline in gas ratio from 35.18% to 38.06% for NOCs is observed during the same period, which is either the result of political pressure for environmental reasons or the different effects of gas ratio on IOCs and NOCs.

This paper aims to investigate the effect of gas ratio on firm-level efficiency for large petroleum companies and to check whether this effect is different in NOCs and IOCs. In the first step, this paper uses the Jackknife model averaging method and two stochastic frontier analysis (SFA) to estimate the input-output relation and derive firm-level

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efficiency, the robustness of which is checked using a data envelopment analysis (DEA) and the adjustment of input categories. Then, the efficiency scores are decomposed using an efficiency determination equation to predict the effect of gas ratio for NOCs and IOCs. The potential endogeneity problems in both SFA and efficiency decomposition are carefully checked and addressed.

There are three central contributions of this paper to the studies of the petroleum industry: 1) the stochastic frontier models used allow non-monotonic time-varying efficiency, which better captures the fluctuations in economy than the frontier models used in the literature; 2) a model averaging method is introduced to combine the advantages of paramedic and semi-parametric estimation of efficiency; and 3) to our knowledge, this is the first study to estimate the efficiency of petroleum companies after the financial crisis, and the first to address the effect of gas ratio. Moreover, the empirical results show that the effect of gas ratio on efficiency is significantly negative and indifferent between IOCs and NOCs, which implies the decline in gas ratio for IOCs is economics-driven, and the incline in gas ratio for NOCs is environment-driven. This paper suggests governments replacing price subsidy with clean energy promotion, which leads to energy saving and emissions reduction.

The remainder of the paper is structured as follows. Section 2 reviews related literature. Section 3 introduces the model. Section 4 describes the data employed. Empirical results are presented and policy implications are given in Section 5. Section 6 draws a conclusion.

2. Literature review

Although the petroleum industry is an important market in the world, very little research to date has studied the productivity and efficiency of oil and gas companies (Eller et al., 2011; Hartley and Medlock III, 2013; Wolf, 2009). Al-Obaidan and Scully (1992) use both deterministic and stochastic frontier analysis (SFA) on cross-sectional data of 44 oil and gas companies to estimate the efficiency. They use assets as the capital input, number of employees as the labor input, and either revenue or physical products as the output to estimate firm-level efficiency, and find NOCs are less efficient than IOCs. Thompson et al. (1996) study the efficiency of 14 major petroleum enterprises in the U.S. oilfield market, using a non-parametric DEA for the period 1980–1991. Gong (2017) introduces spatial techniques into the production function to capture the interactions among oil and gas service companies and then derive total factor productivity (TFP). Gong (2018) evaluates the impacts of new shale techniques (hydraulic fracturing and directional drilling) on SFA-derived firm-level efficiency in the global oilfield service industry. It is worth noting that the last three papers study oilfield service firms rather than petroleum enterprises.

Instead of using firm-level data, Managi et al. (2004) analyze the productivity and efficiency of the offshore Gulf of Mexico oil and gas industry, using well-level and field-level data in a DEA model. A similar dataset is utilized by the same group of scholars in Managi et al. (2006), who adopt a SFA model with the Battese-Coelli (BC) estimator so that time-varying efficiency can be derived. In these two studies, quantities of oil and gas production are used as output variables.

Hartley and Medlock (2008) provide three reasons to use revenue rather than production as output to estimate firm-level efficiency. Firstly, physical output such as oil and gas produced may fail to catch the impact of subsidies (e.g., a lower domestic price) as the result of political pressure on NOCs. Secondly, a usual method to aggregate the multiple products (e.g., oil and gas) is to calculate their relative value at market prices. Thirdly, revenue figures are usually easier to collect than the quantities of various products. Empirically, Wolf (2009) shows the strong correlation between physical outputs and revenue in oil and gas companies. Recent literature (Eller et al., 2011; Hartley and Medlock III, 2013) prefers to use revenue as the output in estimating the efficiency of the oil and gas companies.

In terms of inputs employed for petroleum firms, Al-Obaidan and Scully (1992) use only assets and number of employees. Wolf (2009) adds the sum of oil and gas reserves as the third input to produce oil and gas. Although total assets are kept as an input because they cover other capital than the reserves, Wolf (2009) emphasizes that total assets reflect accounting rather than economic value, which might be severely distorted by inflation. Therefore, Eller et al. (2011) remove total assets from the input portfolio and further separate oil reserves and gas reserves as two different inputs. Finally, Hartley and Medlock III (2013) add refining capacity as an input on the top of the input portfolio in Eller et al. (2011). This paper follows Hartley and Medlock III (2013) by including number of employees, oil reserves, gas reserves, and refining capacity as the four inputs, since this avoids the distortion of total assets mentioned in Wolf (2009), but considers the two most crucial assets including reserves and refining capacity.

Besides inputs and outputs, the last important thing to be decided is the econometrical method that captures the input-output relation. SFA and DEA are the two most widely used methods to estimate firm-level efficiency given inputs and outputs. SFA is a parametric method that allows a stochastic term to control the noise, but requires assumption of the functional form. DEA is a nonparametric linear programming method that relaxes the rigid functional assumption but does not account for statistical noise. They are also the main competing models in the efficiency analysis of the petroleum industry. As mentioned above, Managi et al. (2004) and Managi et al. (2006) employ DEA and SFA to study the offshore Gulf of Mexico oil and gas industry using the same dataset, respectively. Moreover, both DEA and SFA are utilized in Eller et al. (2011) and Hartley and Medlock III (2013). This paper uses different SFA models to estimate firm-level efficiency and a DEA model to check its robustness.

However, the key interest in the literature is the effect of ownership on efficiency. Hartley and Medlock (2008) present a model of NOCs and find they have a wider range of non-commercial objectives, such as domestic consumer surplus and employment. Political pressure forces them to provide domestic subsidy by below-market energy prices and excessive employment, which raises input-output ratio and reduces efficiency. Many scholars (Al-Obaidan and Scully, 1992; Eller et al., 2011; Hartley and Medlock III, 2013; Wolf, 2009) study the difference between NOCs and IOCs, and find that the former group is less efficient than the latter, empirically. Al-Obaidan and Scully (1992) find NOCs on average are only 63–65% as efficient as IOCs. Wolf (2009) also claims that NOCs are 20–30% less efficient than private oil companies. Eller et al. (2011) and Hartley and Medlock III (2013) further introduce an efficiency decomposition equation as a second-step regression after SFA or DEA, aiming to estimate the effect of ownership when other things are equal. Both these studies find a significantly lower efficiency level of NOCs than IOCs. This paper also decomposes efficiency to predict the impact of efficiency determinants more accurately, but with an emphasis on natural gas ratio instead of ownership.

3. Methodology

3.1. Efficiency Measurements

The main approach used by this paper to measure efficiency is stochastic frontier analysis, which was initially proposed by Aigner et al. (1977) and Meeusen and Van den Broeck (1977). Given cross-sectional data, a stochastic frontier production function model equals the deterministic frontier production function plus a symmetric random error variable in the form

$$Y_i = f(X_i)\bullet \mathrm{TE}_i \bullet \exp(\nu_i), \tag{1}$$

where Y_i is the output of firm i, and X_i is the vector of inputs and other regressors. $f(\bullet)$ is the function that decides the frontier, which provides the highest attainable output given inputs. TE_i measures the technical efficiency from 0% to 100%. ν_i is the stochastic part that accounts for measurement errors, which is typically assumed to follow a normal distribution. Assuming Cobb-Douglas form of the production function $f(\bullet)$ and taking the log of Eq. (1) gives the form

$$y_i = x_i{}'\beta - u_i + v_i, \tag{2}$$

where y_i is the output of firm i in logarithms, x_i is a vector of inputs and other regressors in logarithms, and $u_i = -\log(\mathrm{TE}_i)$ is a non-negative random variable since $0 < \mathrm{TE}_i \leq 1$. The efficiency can be derived by $\mathrm{TE}_i = \exp(-u_i)$.

Schmidt and Sickles (1984) propose a stochastic frontier model under a panel data setting when efficiency is assumed to be fixed over time.

$$y_{it} = \alpha + x_{it}'\beta - u_i + v_{it} = \alpha_i + x_{it}'\beta + v_{it}, \tag{3}$$

Then fixed effects or random effects methods can be used to estimate α_i under different conditions, since Eq. (3) is the standard form of the panel data model.

However, the efficiency of a company, or the distance between its actual production and the industry's best practice, is likely to vary across time. Therefore, some scholars have developed new methods to allow a time-variant efficiency in the form

$$y_{it} = \alpha + x_{it}{}'\beta - u_{it} + v_{it} = \alpha_{it} + x_{it}{}'\beta + v_{it}. \tag{4}$$

Based on Eq. (4), Battese and Coelli (1992) propose the error components specification with time-varying efficiencies

$$u_{it} = \exp(-\eta(t - T))\bullet u_i, \tag{5}$$

where $u_{it} \sim N^+(\mu, \sigma_\mu^2)$ is a truncated normal distribution. However, the BC estimator has a monotonicity constraint on efficiency. If η is positive, u_{it} is increasing over time for every firm i, which refers to decreasing efficiency over time. Similarly, negative η and zero η can lead to increasing efficiency and fixed efficiency for all firms, respectively. Moreover, the efficiency changes at the same speed across firms and time, as the change rate $\exp(-\eta)$ is firm-invariant and time-invariant. As a result, this model applies to periods with stable micro and macroeconomic environment, such as the period 2002–2004 in Eller et al. (2011) and most of the period 2001–2009 in Hartley and Medlock III (2013).

This paper studies efficiency changes over the period 2009–2015, during which the petroleum industry gradually gained momentum after the 2007–2009 financial crisis, then experienced another price crash in 2014. The BC estimator may fail to describe both the up and down of the market due to the monotonicity restriction. Hence, this paper introduces two other SFA models that can better capture the non-monotonic fluctuations in the economy that affect efficiency.

Cornwell et al. (1990) propose a quadratic time-varying intercept of all firms on the basis of Eq. (4)

$$\alpha_{it} = \theta_{i1} + \theta_{i2}t + \theta_{i3}t^2, \tag{6}$$

where the quadratic function of time can catch the fluctuation in efficiency affected by business cycles. This Cornwell-Schmidt-Sickles (CSS) model can be solved by a within estimator, which is denoted as CSSW, if the individual effects are assumed to be correlated with the exogenous regressors. Otherwise, the Generalized Least Squares (GLS) estimator, which is denoted as CSSG, is preferred. A Hausman-Wu test can be adopted to choose between CSSW and CSSG.

Kneip et al. (2012) assume that firm-level efficiency is influenced by a set of time-varying factors, and hence model it by a linear combination of some basis functions. More specifically, this Kneip-Sickles-Song (KSS) model assumes the individual effects in Eq. (4) follow

$$u_{it} = \sum_{r=1}^{L} \theta_{ir} g_r(t), \tag{7}$$

where $g_1(t), \ldots, g_L(t)$ are the basis functions, and $\theta_{i1}, \ldots, \theta_{iL}$ are the corresponding parameters. The KSS estimator is derived by semiparametric techniques, which is more flexible than the parametric BC and CSS estiamtors. In fact, the KSS model is a general setting that nests both BC and CSS models. On the one hand, the BC model is a special case of KSS when $g_1(t) = \exp(-\eta(t - T))/\sqrt{\frac{1}{T}\sum_{s=1}^{T}\exp(-\eta(t - T))^2}$ and $L = 1$. On the other hand, the CSS model can be nested in the KSS model when the polynomial functions are the basis functions and $L = 3$.

Endogeneity can be an issue in the CSS and KSS models, since some information witnessed by the petroleum enterprises that is employed in their decision-making process is unobserved to scholars (Ackerberg et al., 2015). Olley and Pakes (1996) and Levinsohn and Petrin (2003) deal with the problem by using observed investment or intermediate inputs to control for unobserved productivity shocks. Their approaches, however, oftentimes suffer from the collinearity problems and hence lead to in pausible results in empirical applications (Ackerberg et al., 2015). This paper chooses the most widely used instrumental variables (IV) method with the endogeneity concern. The control function method introduced in Amsler et al. (2015) is adopted to check whether the inputs are endogenous or exogenous, where input prices and lagged input quantities, as suggested in Levinsohn and Petrin (2003) and Gong (2018), are employed as instruments. If any input is confirmed to be endogenous, the Corrected Two-Stage Least Square (C2SLS) method recommended in Amsler et al. (2015) can be used to correct the bias.

3.2. Model averaging method

There is a tradeoff between the parametric CSS model and the semiparametric KSS model. If the true data generating process (DGP) is close to the assumption in the parametric model (i.e., $\alpha_{it} = \theta_{i1} + \theta_{i2}t + \theta_{i3}t^2$), the CSS estimator outperforms the KSS estimator. However, the KSS estimator is preferred if the rigid assumption of the functional form in CSS is invalid.

Since the true DGP is unobserved, a possible approach is to use some model selection methods to choose between CSS and KSS models. However, various model selection methods under different criteria[1] may lead to different selection results. Even under the same criteria, a slight change in data may lead to completely different selection. Furthermore, all the candidate models, rather than only one of them, may reflect the underlying DGP to some extent (Shang, 2015). Therefore, model averaging methods that assign a weight to each candidate model according to its ability to explain the data, rather than treating a single model as the "best", are better tools to approximate the underlying mechanism and describe the true DGP. It is worth noting that model selection is a special case of model averaging procedure, when all the zero weight is assigned to all but one candidate models.

There are several weight-determination techniques in the literature. The information criteria-based approach can be utilized in model averaging method (Buckland et al., 1997). However, it is hard to test for effectiveness and quality improvement. Hansen and Racine (2012) propose a Jackknife-based model averaging method, which is asymptotically optimal and approaches the minimum expected square errors when the sample size approaches infinity. Substantially, the Jackknife method assigns weights based on the "leave-one-out" cross-validation criterion.

This paper first derives the "leave-one-out" cross-validation for CSS and KSS, respectively. The Jackknife estimators of the output $\hat{y}^{\mathrm{CSS}} = (\hat{y}_1^{\mathrm{CSS}}, \ldots, \hat{y}_n^{\mathrm{CSS}})$ and $\hat{y}^{\mathrm{KSS}} = (\hat{y}_1^{\mathrm{KSS}}, \ldots, \hat{y}_n^{\mathrm{KSS}})$ are predicted, where $\hat{y}_i^{\mathrm{CSS}}$ and $\hat{y}_i^{\mathrm{KSS}}$ are the fitted value of company i's output using the CSS and KSS method, respectively, when the i-th firm is deleted from the dataset. Suppose the weight for CSS is w, the weight for KSS is $1-w$ accordingly. The Jackknife weight w^* can be achieved by minimizing the cross-validation criteria:

$$w^* = \underset{0 \leq w \leq 1}{\operatorname{argmin}}\, CV_n(w) = \frac{1}{n}\hat{e}(w)'\hat{e}(w), \tag{8}$$

[1] Popular criteria include, but not limited to, the Akaike information criterion (AIC), the Bayesian information criterion (BIC), and the Focused information criterion (FIC).

where $\hat{e}(w) = y - w\hat{y}^{CSS} - (1-w)\hat{y}^{KSS}$.

Then, the model averaging stochastic frontier model this paper adopted has the form:

$$y = w^* y^{CSS} + (1-w^*) \quad y^{KSS}, \tag{9}$$

where y^{CSS} is the CSS estimator follows Eqs. (4) and (6), and y^{KSS} is KSS estimator follows Eqs. (4) and (7). The intercept, coefficients, and efficiency terms are all the Jackknife-weighted average of the CSS and KSS estimators.

3.3. Robustness checks

This paper checks the robustness of the efficiency estimates and the model averaging method in the petroleum dataset. x_{it}' in Eq. (4) vector inputs of the oil companies including number of employees, oil reserves, gas reserves, and refining capacity, as well as other repressors including oil price realization and gas price realization, which is denoted as a "four-input model." In the first robustness check, this paper follows Wolf (2009) to treat total reserves in million barrels of oil equivalent (BOE) as an input, which measures the overall resources held by a company. Replacing the oil and gas reserves with total reserves, the CSS and KSS estimators are re-estimated, followed by the Jackknife model averaging method. The robustness of the efficiency estimates and the model averaging weights can be tested using this "three-input model."

To this end, this paper uses stochastic frontier models. Although the individual effects of the KSS approach are modeled semi-parametrically, the production frontier is assumed to follow a Cobb-Douglas form. The aforementioned tradeoff between parametric and semi-parametric individual effects in CSS and KSS models also applies to the assumption of the production frontier. If the true input-output relation in the petroleum industry is very different from the Cobb-Douglas form, the efficiency estimated can be inaccurate. Implementing a nonparametric representation of the frontier is another way to estimate efficiency. The most widely used nonparametric approach is DEA, which is the major competing methodology to SFA in efficiency analysis.

DEA is a linear programming method that is powerful and easy, and imposes minimal assumptions on the boundary of the input requirements set, including piece-wise linearity and convexity. The efficiency can be estimated by solving the linear programming problem:

$$D_{it}(y_{it}, x_{it}) = \min_{\theta,\lambda} \theta, \tag{10}$$

$$\text{s. t.} \quad -y_{it} + Y\lambda \geq 0, \quad \theta x_{it} + X\lambda \geq 0, \quad \lambda \geq 0,$$

where λ is a vector of constants. Substantially, this linear program radially contracts the input vector of each company to a projected point $(X\lambda, Y\lambda)$, on the surface of the piece-wise linear isoquant that represents the frontier. The efficiency score of firm i at time t is given by $0<\theta \leq 1$, which is comparable with those estimated in the SFA models. Therefore, this paper utilizes this DEA model to check the robustness of the efficiency derived from the weighted average of the CSS and KSS estimators.

3.4. Decomposition of efficiency

This paper is interested in the effect of natural gas ratio in portfolio on firm-level efficiency in the petroleum industry. Since the dependent variable, the firm-level efficiency, is in percentage from 0% to 100%, a Tobit regression model is introduced to estimate the efficiency determination equation.

$$Eff_{it} = \alpha + \beta gas_{it} + \rho noc_{it} + \eta gas_{it} noc_{it} + \gamma seg_{it} + \delta reg_{it} + \tau year_t + \varepsilon_{it}. \tag{11}$$

where Eff_{it} is the firm-level efficiency for firm i at time t, and gas_{it} is the ratio of natural gas in production that measures the share of crude oil and natural gas in portfolio of a company (i.e., output share by product). noc_{it} is a dummy variable of the NOCs. Since different trends of gas_{it} between NOCs and IOCs are observed, this paper checks the potential heterogeneous effects of gas_{it} on efficiency for NOCs and IOCs by adding an interaction term $gas_{it} noc_{it}$. Moreover, it is necessary to control each company's output share by segment and output share by region, as many energy companies are found to be multi-segment/product firms (Hawdon, 2003; Jacobsen et al., 2006; Seeto et al., 2001) or multi-region/national firms (Bertoldi et al., 2006; Bilgin, 2007; Conway, 2013; Fontaine, 2011). seg_{it} is a vector that measures the output share in each segment, respectively. reg_{it} is a vector that measures the output share in each region, respectively. $year_t$ is a vector of year dummy variables to control the time effects.

Endogeneity may also be an issue in the efficiency determination equation due to omitted variable bias and simultaneity bias. On the one hand, this paper adds some other efficiency determinants into Eq. (11) besides the variables of gas ratio and ownership to check the omitted variable bias. On the other hand, simultaneity bias is another concern as some efficiency determinants may be conversely affected by efficiency. For instance, more efficient companies are more successful and are more likely to step into a new segment or region. As a result, efficiency may affect output share by segment and by region. This paper replaces all efficiency determinants in Eq. (11) with their lagged values to deal with the causality problem, which can also be treated as a robustness check.

4. Data

The primary data source is the Energy Intelligence's "*Top 100: Global NOC & IOC Rankings*". The variables required in SFA and DEA, including firm-level revenue (in billion US dollars), number of employees, oil reserves (in million barrels, MMbbl), gas reserves (in billions cubic feet, Bcf), refining capacity (thousand barrels per day, '000 b/d), oil price realization (US dollars per barrel of oil equivalent, \$/BOE), and gas realization (US dollars per thousand cubic feet, \$/Mcf), are all available in this dataset. This dataset also reports firm-level oil production (in thousand barrels per day, '000 b/d) and gas production (in million cubic feet per day, MMcf/d), which can derive the ratio of natural gas in production. Moreover, another efficiency determinant of interest, the output share by segment, can be calculated, since this dataset provides oil and gas produced in the upstream segment, oil and gas refined in the refining segment, and oil and gas sold in marking segment. Finally, this dataset has firm category information to separate NOCs and IOCs. The last set of efficiency determinants, output share by region, are collected from Rystad Energy's UCube database, where production from Asia-Pacific, Middle East, Africa, America, Europe, and Russia is given for each company-year observation, respectively.

Although Energy Intelligence's "*Top 100: Global NOC & IOC Rankings*" include one hundred biggest oil companies in the world from 2009 to 2015, this paper drops firms with missing input or output information. A balanced panel data of 54 companies covering 2009–2015 remains, which is comparable with the sample of 44 petroleum enterprises for 1979–1982 in Al-Obaidan and Scully (1992), the sample of 14 integrated oil companies for the years 1980–1991 in Thompson et al. (1996), the sample of 50 largest oil companies over the period 1987–2006 in Wolf (2009), the sample of 78 oil firms during the period 2002–2004 in Eller et al. (2011), and the sample of 61 oil companies from 2001 to 2009 in Hartley and Medlock III (2013). Among these 54 companies, 16 are NOCs and 38 are IOCs.

Table 1 summarizes firm-level inputs and outputs, oil and gas price realizations, and efficiency determinants in the years 2009 and 2015, respectively. The average annual revenue of these oil companies decreased slightly from 55.73 billion to 55.25 billion US dollars in seven years. Among the four inputs, only the oil reserves increased more than one quarter, while the number of employees, the gas reserves, and the refining capacity all decreased over the period 2009–2015. Due to the

Table 1
Summary statistics.

Variable	Explanation	Unit	2009	2015	Changes
y	Revenue	billion $	55.73	55.25	−0.86%
Labor	Number of employees	’000	79.81	75.45	−5.46%
OilRsv	Oil reserves	MMbbl	7505	9472	26.21%
GasRsv	Gas reserves	Bcf	30401	29951	−1.48%
RefCap	Refining Capacity	’000 b/d	915.2	832.5	−9.04%
OilPr	Oil price realization	$/BOE	54.24	40.62	−25.11%
GasPr	Gas price realization	$/Mcf	3.99	3.72	−6.77%
gas	Ratio of natural gas in portfolio	%	42.69	40.96	−4.05%
*seg*1	Share in upstream segment	%	57.51	64.19	11.62%
*seg*2	Share in refining segment	%	20.03	16.70	−16.63%
*seg*3	Share in marking segment	%	22.46	19.12	−14.87%
*reg*1	Share in Asia-Pacific	%	22.33	20.81	−6.81%
*reg*2	Share in Middle East	%	4.86	6.56	34.98%
*reg*3	Share in Africa	%	10.35	7.33	−29.18%
*reg*4	Share in America	%	41.33	45.82	10.86%
*reg*5	Share in Europe	%	8.41	6.39	−24.02%
*reg*6	Share in Russia	%	12.72	13.09	2.91%

price crash since 2014, the average price realization of oil and gas in 2015 was 25.11% and 6.77% lower than the level of 2009, respectively. The ratio of natural gas in oil companies’ portfolios on average decreased from 42.69% to 40.96%, indicating a smaller share of natural gas in the total production of the large oil companies. The upstream segment is the largest segment and keeps expanding, while refining and marketing segments are smaller and diminishing, which shows the behavior of the large oil companies in favor of the upstream business in recent years. Geographically, more than 40% of the production of these 54 large oil companies is from America, and Asia-Pacific contributes to one-fifth of their total production.

5. Results and discussion

5.1. Stochastic frontier and model averaging

Following Eller et al. (2011) and Hartley and Medlock III (2013), this paper assumes that the production technology exhibits constant returns to scale (CRS). The endogeneity of inputs in the production function is tested and the result shows that all the inputs are exogenous. As the first step, a Hausman-Wu test is employed to choose between the CSSW and CSSG, which generates a p-value of 0.5018 in favor of the CSSG model. In the first robustness check, when oil reserves and gas reserves are aggregated as a single input, the Hausman-Wu test generates a p-value of 0.9695, which again suggests using the CSSG model. Therefore, this paper uses CSSG and KSS to calculate the firm-level efficiency of oil companies and then estimate the Jackknife model averaging weights accordingly. Table 2 provides the estimation results of the CSSG, KSS, and Jackknife-weighted average stochastic frontier model. The first and third columns in Table 2 present the CSSG and KSS estimator of the “four-input model”, respectively. Then, the fifth column reports the Jackknife-weighted average stochastic frontier model accordingly. The second, fourth, and sixth columns in Table 2 provide the estimation results of the “three-input model” as a robustness check, which is comparable with the first, third, and fifth column, respectively.

In Table 2, the Jackknife weight of CSSG is 0.2760 in the “four-input” model, which implies both CSSG and KSS can explain the data-generating process to some extent, but the semi-parametric KSS is more important. The robustness of this conclusion is supported, as the Jackknife weight of CSSG is 0.2161 in the “three-input” model. As a result, the fifth column reports that the coefficients of labor, oil reserves, gas reserves, and refining capacity are 0.292, 0.164, 0.451, and 0.094, respectively, which are all significantly positive. The contributions of labor and reserves are greater than that of the refining capacity. Moreover, the oil price has a significantly positive effect on output, while the effect of natural gas price is insignificant both statistically and economically. The results in the sixth column also confirm the aforementioned findings on inputs and prices.

5.2. Firm-level efficiency

The stochastic frontier regressions in the fifth and sixth column of Table 2 can further derive firm-level efficiency of the “four-input” and “three-input” models, which are denoted as Eff_1^{SFA} and Eff_2^{SFA}, respectively. As the second robustness check, this paper also uses DEA in the “four-input” and “three-input” models to derive firm-level efficiencies, which are denoted as Eff_1^{DEA} and Eff_2^{DEA}, respectively. Table 3 summarizes the distribution of the efficiency scores in the international petroleum industry under the four models. In summary, the efficiencies estimated by the DEA model and the “four-input” model are slightly higher.

In order to check the robustness of the efficiency estimated in the main model (Eff_1^{SFA}), this paper calculates the correlation of efficiencies for the four models in Table 4. All the correlation coefficients in the table are above 0.7, which implies a strong uphill (positive) linear relationship across the efficiencies derived in the four models. Furthermore, Table 5 reports the estimation results of three Tobit regressions, where Eff_1^{SFA} is the independent variable and the other three groups of efficiencies (Eff_1^{DEA}, Eff_2^{SFA}, and Eff_2^{DEA}) are the dependent variables, one for each regression. The result also verifies the robustness of the efficiency scores under different methods.

To this end, this paper estimates the production frontier and derives firm-level efficiencies. The robustness of the firm-level efficiencies is also confirmed using different methods (SFA vs. DEA) and input portfolios (aggregate vs. disaggregate reserves). The fact that various approaches yield similar estimations should increase confidence that the efficiencies reflect genuine underlying differences among petroleum enterprises. This paper uses the robust efficiency estimated in the main model (Eff_1^{SFA}) for efficiency decomposition analysis.

5.3. Efficiency decomposition

The most important question this paper seeks to answer is whether or not investing more in natural gas will decrease firm-level efficiency, which reflects the economic impact of producing this clean energy; and, moreover, whether or not this effect is different in NOCs and IOCs, as the former have been increasing share of gas while the latter have reducing share of gas in recent years. Finally, the impacts of the other two sets of efficiency determinants, the output share by segment and by region, can provide valuable information as well. Table 6 reports the estimation results of the efficiency determination equation. Columns (1)–(4) are estimations of the regular Tobit model where different sets of independent variables are utilized to check the robustness of the results. Column (5) presents the results of the full model in Eq. (11) to avoid omitted variable bias. Column (6) replaces the independent variables with their lagged values to deal with the simultaneous bias, which has fairly robust results.

All the six columns in Table 6 report a significantly negative coefficient of natural gas share in portfolio, indicating more investment in this clean energy will lower firms’ efficiency. Therefore, the large oil companies reduced the share of clean products in the context of environmental protection, because of economic and commercial concerns. Another robust finding is that NOCs are significantly less efficient than IOCs, holding other factors fixed. However, the magnitude of the difference between NOCs and IOCs is smaller than that found in the literature that uses earlier data.

The follow-up question, whether or not the effect of natural gas share in portfolio is different for NOCs and IOCs, is answered by columns (4)-(6) in Table 6, where insignificant estimates of the interaction

Table 2
Estimation results of the stochastic frontier models.

	CSSG		KSS		Jackknife Average	
	Four-input	Three-input	Four-input	Three-input	Four-input	Three-input
Labor	0.393***	0.344***	0.253***	0.199***	0.292***	0.230***
	(0.013)	(0.012)	(0.028)	(0.027)	(0.025)	(0.025)
OilRsv	0.218***	–	0.144***	–	0.164***	–
	(0.010)	–	(0.039)	–	(0.034)	–
GasRsv	0.300***	–	0.508***	–	0.451***	–
	(0.009)	–	(0.043)	–	(0.037)	–
TotalRsv	–	0.581***	–	0.735***	–	0.702***
	–	(0.010)	–	(0.031)	–	(0.028)
RefCap	0.090***	0.075***	0.095***	0.066***	0.094***	0.068***
	(0.006)	(0.005)	(0.023)	(0.021)	(0.020)	(0.019)
OilPr	0.307***	0.299***	0.059	0.033	0.127***	0.090*
	(0.018)	(0.017)	(0.061)	(0.057)	(0.053)	(0.051)
GasPr	0.092**	0.080*	0.020	−0.005	0.040	0.013
	(0.044)	(0.041)	(0.061)	(0.057)	(0.057)	(0.054)
*w**	–	–	–	–	0.2760	0.2161

Notes: Significant at: *10, * *5 and * * * 1 percent; Standard error in parentheses.

Table 3
Technical efficiency statistics.

	Four-input model		Three-input model	
	Eff_1^{SFA}	Eff_1^{DEA}	Eff_2^{SFA}	Eff_2^{DEA}
Mean	0.46	0.55	0.45	0.47
Minimum	0.12	0.02	0.10	0.02
25% quantile	0.29	0.28	0.25	0.23
50% quantile	0.42	0.54	0.38	0.42
75% quantile	0.60	0.81	0.63	0.65
Maximum	1.00	1.00	1.00	1.00

Table 4
Correlation of efficiencies across models.

	Eff_1^{SFA}	Eff_1^{DEA}	Eff_2^{SFA}	Eff_2^{DEA}
Eff_1^{SFA}	1	0.8156	0.9036	0.7917
Eff_1^{DEA}	0.8156	1	0.7354	0.8940
Eff_2^{SFA}	0.9036	0.7354	1	0.8398
Eff_2^{DEA}	0.7917	0.8940	0.8398	1

Table 5
Robustness of the efficiencies across models.

	Eff_1^{DEA}	Eff_2^{SFA}	Eff_2^{DEA}
Eff_1^{SFA}	0.822***	0.914***	0.801***
	(0.059)	(0.045)	(0.050)
Constant term	0.185***	0.037*	0.093***
	(0.029)	(0.022)	(0.025)

term *gas•noc* imply indifferent effect regardless of ownership. In other words, improvement of natural gas share has a negative impact on commercial performance for both NOCs and IOCs. Therefore, IOCs are reducing share of natural gas, as expected, for economic reasons. However, NOCs are still expanding natural gas share in portfolio in spite of the financial sacrifice.

Such difference in behaviors between NOCs and IOCs indicates a third non-commercial objective of the NOCs, which is the environmental objective. Hartley and Medlock (2008) argue that NOCs have two noneconomic objectives, namely excessive employment and below-market prices, as the result of political pressure. These two actions can be regarded as subsidies to the domestic workforce and consumers in reward for the loss in firm-level efficiency, which is confirmed in Eller et al. (2011) and Hartley and Medlock III (2013). The NOCs' behavior of adding investment in the cleaner natural gas found in this paper is likely to be a subsidy to domestic residents under political pressure for a better environment. As a comparison, the IOCs have less political pressure on them, and hence reduce share of natural gas for economic purposes. In summary, the different behaviors of IOCs and NOCs are economics-driven and environment-driven, respectively.

Besides the output share by product, Table 6 also predicts the effects of output share by segment and by region on firm-level efficiency. Vertically, the marking segment is more efficient than the upstream and refining segments, hence increasing the share of marking can raise firm-level efficiency. Geographically, companies that have more footprints and activities in Asia-Pacific, Africa, America, and Europe are likely to outperform in efficiency. Although not reported in Table 6, the estimations of the year dummy variables are robust across the five columns. The average efficiency increased in 2010 and 2011, but decreased over the period of 2012–2015. This non-linear and non-monotonic trend verifies the necessity of using CSS and KSS models, rather than the BC model in Hartley and Medlock III (2013). Detailed estimations of the year dummy variables are available on request.

6. Conclusion and policy implications

Natural gas is usually compared with coal and renewable energy, as they are the competing sources in electricity generation. However, its main competitor is crude oil from the supply side, since petroleum enterprises can decide the share of natural gas and crude oil in their portfolios. Moreover, oil and gas are competing in the automobile market. This paper finds large oil and gas companies on average are reducing share of natural gas because producing gas is not as efficient as producing oil in both NOCs and IOCs. As the investment in and expenditure on crude oil are increasing, the gap between oil and gas can be enlarged, which will, in turn, further discourage R&D and the production of natural gas.

The political pressure around environmental concerns can affect the behavior of NOCs, but has achieved limited influence on IOCs to date. On the one hand, governments may adjust the relative tax rate for crude oil and natural gas in favor of the latter. On the other hand, governments can adjust its R&D distribution between crude oil and natural gas to increase the productivity of gas extraction. These actions could be more effective than environmental pressure on IOCs, as this paper has shown that the commercial objective is the priority for this cohort.

Table 6
Estimation results of the efficiency determination regressions.

	(1)	(2)	(3)	(4)	(5)	(6)
gas	−0.124**	−0.267***	−0.179***	−0.240***	−0.144**	−0.125*
	(0.060)	(0.061)	(0.062)	(0.066)	(0.066)	(0.072)
noc	–	−0.177***	−0.177***	−0.118*	−0.100*	−0.121*
	–	(0.030)	(0.030)	(0.062)	(0.059)	(0.065)
gas•noc	–	–	–	−0.180	−0.233	−0.154
	–	–	–	(0.164)	(0.157)	(0.170)
*seg*1	–	–	−0.329***	–	−0.339***	−0.283***
	–	–	(0.105)	–	(0.105)	(0.106)
*seg*2	–	–	−0.379	–	−0.396*	−0.268
	–	–	(0.240)	–	(0.240)	(0.238)
*reg*1	0.114*	0.281***	0.246***	0.295***	0.262***	0.265***
	(0.059)	(0.062)	(0.061)	(0.064)	(0.061)	(0.065)
*reg*2	0.102	0.064	0.048	0.056	0.036	0.049
	(0.099)	(0.094)	(0.090)	(0.094)	(0.090)	(0.097)
*reg*3	0.358***	0.369***	0.328***	0.377***	0.338***	0.296***
	(0.087)	(0.082)	(0.080)	(0.082)	(0.080)	(0.086)
*reg*4	0.183***	0.253***	0.257***	0.243***	0.244***	0.239***
	(0.049)	(0.048)	(0.046)	(0.049)	(0.047)	(0.050)
*reg*5	0.537***	0.649***	0.570***	0.647***	0.567***	0.563***
	(0.084)	(0.081)	(0.081)	(0.081)	(0.080)	(0.086)
Year effects	Yes	Yes	Yes	Yes	Yes	yes
Intercept	0.355***	0.386***	0.632***	0.376***	0.627***	0.564***
	(0.049)	(0.046)	(0.118)	(0.047)	(0.118)	(0.117)

Notes: Significant at: *10, * *5 and * * * 1 percent; Standard error in parentheses.

How to make the NOCs more efficient and competitive relative to IOCs is another challenge faced by governments. This paper shows the efficiency difference between NOCs and IOCs is decreasing as time goes by. Excessive employment is not purely a political burden, but implies massive potential human capital. Training workers' skills and developing their experience can encourage innovation in NOCs, and hence improve their productivity and efficiency, especially in the context of the shale technical revolution.

Moreover, there are tradeoffs among below-market energy prices, excessive employment, and more clean products. When maintaining efficiency at a certain level, governments can adjust the amount of these subsidies. In the context of energy saving and environmental protection, governments may consider cutting the energy price subsidy, while encouraging more production of natural gas. The former action can reduce the total consumption of energy and the volume of emissions, while the latter can increase the share of cleaner energy in portfolio and hence further decrease emissions intensity. As domestic consumers and residents have become more aware of environmental protection and emissions reduction in recent years, such transfer of subsidies is facing fewer obstructions.

In summary, the paper aims to explore the impact of gas ratio on firm-level efficiency for large petroleum companies during the period 2009–2015. A Jackknife-weighted average of CSS and KSS models helps derive firm-level efficiency more accurately. The derived efficiency is then decomposed to predict the effect of various efficiency determinants with an emphasis on gas ratio and ownership. To our knowledge, this is the first study to analyze the efficiency of the petroleum industry after the financial crisis, and the first to explain the different behaviors on natural gas ratio for NOCs and IOCs.

Using a panel data of 54 large oil and gas companies, the effect of gas ratio on efficiency is found to be significantly negative. Moreover, this impact is indifferent between IOCs and NOCs. These findings imply that the decline in gas ratio for IOCs is economics-driven, and the incline in gas ratio for NOCs is environment-driven. Hence, the environmental objective is the third non-commercial objective of NOCs after the subsidies of below-market energy prices and excessive employment found in the literature. Finally, governments may consider the transfer of subsidies from energy price to clean energy promotion, which leads to energy saving and emissions reduction.

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