The End of Easy Oil: Estimating Average Production Costs for Oil Fields around the World

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ABSTRACT

This paper develops empirical models for average oil production costs that represent the structural field-level and country-level determinants most characteristic for the new era beyond easy oil. These models lend themselves as a tool for forecasting the floor of structural cost trends related to the shift into more cost intensive fields that are increasingly producing heavy and extra-heavy crudes and that are located offshore and in countries fraught with high levels of political and environmental risks. Given the extremely limited availability of reliable, non-proprietary cost data, this model deliberately relies on high level factors for which data is publicly available for hundreds of fields from all oil producing states. This model specification offers the important advantage of enabling us to lever insights gained from this study in powerful out-of-sample estimations for the dominant scenario where data is available on field characteristics but not on costs.

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1. INTRODUCTION

The specter that we are running out of oil has been haunting the world economy ever since Pennsylvania's oil output peaked in 1891. But as Adelman and others have argued convincingly over the past forty years, the oil industry will run out of customers long before hydrocarbon resources have been depleted (Adelman 2002, 172). With oil prices continuing their stellar rise, investments in energy efficiency and alternative sources of energy are increasing in attractiveness. OPEC's control over most of the world's comparably cheap oil fields along with the exploding energy demand of China and other emerging markets are accelerating this transition. Simultaneously, in a wave of re-emerging resource nationalism international oil companies are finding themselves locked out of many attractive fields and relegated to fields governments of oil rich states consider technically too challenging or too risky for their domestic national oil company. As a consequence, an ever increasing share of global production, in particular outside of OPEC, comes from technically complex fields that produce very heavy crudes and that are located offshore and in countries fraught with high levels of environmental and political risks. Understanding the cost implications of this transition into an era beyond easy oil is paramount for forecasting future supply, and by extension, also of price. The importance of reaching a better understanding of the cost fundamentals contrasts sharply with the scarcity of empirical work in this area. The main reason for this knowledge gap is the paucity of publicly available disaggregated[2], non-proprietary[3] cost data. While the theoretical literature has made significant advances since Hotelling's path-breaking study of 1931 on the economics of exhaustible resources (e.g. Kuller and Cummings 1974; Halvorsen and Smith 1984; Heaps 1985), empirical

[2] Most of the open source data on production cost is aggregated on a regional level (e.g. data compiled by the US Energy Information Administration (EIA) based on data submissions by oil companies under the Financial Reporting System).
[3] A number of oil consultancies (e.g. WoodMcKenzie or IHS) compile field-level datasets, but access is restricted to their clients.

studies modeling average production costs for hydrocarbon remain rare[4].

This paper seeks to contribute to our empirical understanding of the factors that affect average production costs and thus to strengthen our ability to assess the cost implications of the ongoing move into technically challenging fields. It does so by developing a field level model for the cost drivers most commonly cited in the petroleum engineering and natural resource economics literature—namely field specifics and location factors—based on data for 90 oil fields from 24 countries. This choice of predictors helps us explain why some fields are more expensive to produce than others and to forecast the floor of structural cost trends. The models presented here are less suited for analyzing cyclical cost volatility driven by bottlenecks or overcapacity in input factors that result from fast and unanticipated change of exploration and development (E&D) activities[5]. This study focuses deliberately on high level explanatory variables for which data is publicly available for hundreds of fields from around the world and over many years. This model specification offers the important advantage of enabling us to lever the insights gained from this study in out-of-sample estimations of field level production costs for the dominant scenario where we have data on technical field characteristics but not on costs. Also, the great public availability of historic data for the predictors used here allows for extrapolating structural cost trends. The obvious drawback of this approach is that the ability of these high level variables to account for the full variance in production costs is limited. However, as I hope to show in the following, the models presented in this paper strike a good balance between achieving high explanatory power and maximizing their applicability to a large number of fields from around the world.

[4] Among the few empirical economists that research production costs in the upstream petroleum industry most position their analysis on the country level (e.g. Adelman and Shahi 1989; Stauffer 1999) or the state, or province level (e.g. Adelman 1992). A few recent studies have analyzed costs on a well level (Chermak and Patrick 1995; Bloomfield and Laney 2005; Foss and Gordon 2007) with disaggregate data of limited availability.

[5] For instance, the cost explosion of more than 50% in the past two years is primarily to be attributed to sever industry capacity constraints (e.g. in offshore rigs) that tightened under the pressure of the current E&D frenzy (IHS 2007). The cost increase of this magnitude and suddenness was only secondarily caused by the concurrent increase in unconventional oil operations.

The argument proceeds in five stages. The next section introduces the model and motivates the selection of variables with reference to the current petroleum engineering and natural resource economics literature. Section III presents the data and the sources from which it was retrieved. The main part of this study—section IV—is dedicated to the testing of 11 different models. Section V summarizes the key findings of this study and highlights their implications for production costs in the era of non-easy oil.

2. CONCEPTUAL FRAMEWORK AND DEFINITIONS

This paper seeks to estimate the impact of various technical factors on average production costs, thereby helping us to understand cost differences across fields. This paper does not explicitly model the cost minimizing combination of input factors (capital, labor, energy, and materials). Rather, it treats firms' cost functions as a black box and assumes that the costs provided in the dataset used here present the cost optimal input combination chosen by profit maximizing companies[6], without knowing the actual factor combination companies chose for developing and operating their fields. The dependent variable of this paper's models—i.e. average production costs (*costs_t*)—is the sum of all technical costs related to the finding, development, and lifting of an oil field divided by the volume of oil that is expected to be recovered from the field over its lifetime. These production costs are the aggregate of four cost categories. A first element are finding costs, which the data source used here—i.e. the Goldman Sachs "Top 125" report of 2006 (see section 3)—conceptualizes largely in line with the definition provided by the United States Energy Information Administration (EIA)[7]. Secondly, development costs include expenses directly related to the development of a particular field, including the drill-

[6] This assumption is justifiable given the fact that all of the fields analyzed here (except the Sonatrach operated Ourhoud field in Algeria) are operated by publicly traded oil companies and thus subject to shareholder pressure to maximize efficiency.

[7] The EIA defines finding costs as "the costs of adding proven reserves of oil and natural gas via exploration and development activities and the purchase of properties that might contain reserves" (EIA 2006, 25). N.B.: The finding costs provided by the Goldman Sachs "Top 125" report includes only very limited exploration activity and no historic exploration costs (correspondence by author).

ing of production wells, installation of platforms, wellheads, subsea equipment etc., and the construction of pipelines connecting the field to a main transport pipeline or processing plant. Lifting costs (in some publications also called production or operating costs) represent the third element of the production cost variable used in this paper. They refer to "out-of-pocket costs per barrel of oil ... to operate and maintain wells and related equipment and facilities after hydrocarbons have been found, acquired, and developed for production" (EIA 2006, 23). Forth and finally, capital expenditures on infrastructure like major transport pipelines, terminals, and processing plants are also included. I deliberately exclude payments to governments that are specific to oil operations (e.g. signature bonuses, royalties, profit oil, and resource rent taxes[8]), so as to provide a better basis for estimating the magnitude of potential oil rents and for the design of an optimal fiscal regime (Hotelling 1931; Gaffney 1967; Deacon 1993).

Based 0n the extant petroleum engineering and resource economics literature, this study identifies two categories of variables as the most promising candidates for explaining differences in production costs: field specifics and characteristics of the wider operational environment.

Within the first category of explanatory variables, i.e. field specifics, I examine a total of four different cost variables. First, important quality differences exist within one and the same exhaustible resource category, which in turn affects not only the price of these resources but also their production costs (Gordon 1975; Solow and Wan 1976). The most cost-relevant quality aspect is the relative density of petroleum liquids, measured in degrees of API[9] gravity. I therefore explicitly introduce API gravity as the central resource attribute parameter in my model. The second field level cost variable—depletion rate—is assumed to be positively correlated with production costs. Faster extraction risks a more pronounced pressure drop in the reservoir, thus accelerating the need for costly enhanced recovery measures and ultimately for field abandonment (Craft and Hawkins 1959). This paper takes

[8] For of data limitation reasons, this study cannot filter out value added taxes imposed on supplies or crypto taxes.
[9] American Petroleum Institute

this factor into account by including a model variable that captures a field's depletion rate (*ppr*, measured as annual production volume per total proved reserves[10]). A third field level cost factor commonly discussed in the literature relates to the field's location, specifically to whether a field is located onshore or offshore. Most of the literature stresses the high costs associated with the development of offshore fields (e.g. le Leuch and Masseron 1973), even though the cost difference between offshore and onshore has decreased significantly over the past three decades (Babusiaux et al. 2004, 143; Birol and Davie 2001) . To test the hypothesis that production is *ceteris paribus* more expensive offshore than onshore, this study's models include a location dummy variable (*offshore*, which takes on the value of 1 if the field is offshore and 0 otherwise). The fourth and final variable in the category of field-specific cost variables comes from Chermak and Patrick's (1995) empirical study which suggests that production costs decreased with increasing production volumes per well (*wells_n*). This is assumption is based on the fact that drilling often accounts for almost a third of total development costs (Babusiaux et al. 2004).

The second category of explanatory variables captures relevant characteristics of a field's wider operational environment. Specifically, the model distinguishes between environmental hazards (*hazard*)—namely earthquakes, volcanoes, landslides, floods, drought, and cyclones—and political risk. The damage hurricane Katrina caused to oil platforms in the Gulf of Mexico is only one of many examples reminding us of the significant losses natural events can cause (see Kaiser 2007). The second country-level variable refers to the political risk oil companies face when operating in poorly governed countries. Conventional wisdom suggests that higher political risk results in higher costs through a higher risk premium investors demand. Political risk is particular relevant for petroleum companies, as most of their investments are asset specific and with a long pay-back period, making them particularly vulnerable to expropriations, conflict-induced shut-ins, and opportunity costs

[10] Other studies capture a similar idea with an alternative metric, namely the share of remaining resources in a given field (Livernois and Uhler 1987; Chermak and Patrick 1995).

caused by legal uncertainty in poorly governed states (Nitzov 2004). As discussed in more detail below (see section 3 and 4.3), I will examine both firm specific instability risks (Berlin 2003) such as bunkering, sabotage, and kidnapping (e.g. Nigeria) (*icrg_law*, *wgi_law)* and more aggregate political risks (*icrg_agg*, *wgi_ave*) which also include risks posed by political institutions of poor quality. The theoretical literature suggests that the extent to which such risks affect oil operations is conditioned upon a field's location. Political risk is thereby assumed to be of smaller importance for offshore fields, because platforms surrounded by sea are easier to protect against insurgents and criminals than onshore fields like Shell's fields in the swamplands of the Niger delta (Boschini, Petterson and Roine 2007). This effect will be measured by the interaction term *off_pol*, which is the product of *offshore* and *pol_risk*.

The model also includes dummy variables to capture geography specific factors, other than those explicitly captured by the other explanatory variables. I differentiate between five world regions, namely sub-Saharan Africa (*ssa*), the Western Hemisphere encompassing both Latin America and North America (*west*), Eurasia including Europe and the successor states of the former Soviet Union (*eurasia*), South and East Asia (*asia*), and the Middle East and North Africa (*mena*) (see also 4.3). Conventional wisdom suggests *mena* to be the region with the lowest average production costs (IEA 2005).

3. DATA

This paper uses Goldman Sachs' "Global Energy–125 Projects to Change the World" report of 2006 as its primary data source. This report presents the most promising development projects in the oil and gas industry and is unique among the publicly available sources as it provides non-aggregated, i.e. field level, data on production costs and on a range of cost relevant technical data. For the sample underlying the models presented in the next section I excluded all fields that are primarily gas fields[11], as some of the explanatory variables (e.g. API gravity) used here are only relevant for oil fields. Two additional fields[12] had to be dropped because they are located in countries whose political risk has so far not been assessed. This leaves us with a dataset of 90 fields from 24 countries, whereby Canada, Nigeria and Angola are the countries with the largest number of fields included in the report (11, 11 and 10 fields, respectively).

The Goldman Sachs report provides comprehensive data on the fields' location and on their depletion rate but only incomplete data on crude gravity (30 fields) and the number of wells (66 fields). For another 58 fields, I obtained API gravity data from a number of industry sources[13] and by imputing API gravity as a simple average of crudes from the same country based on data from the Oil and Gas Journal Data Book of 2006. I found data on the number of wells only for one additional field listed in the Goldman Sachs report[14]. For the country level variable *hazard* I used data from Columbia University's Natural Disaster Hotspots database on the share of countries' territory that is exposed to multiple natural hazards. Data on political risk is taken from two different sources and at two different levels of aggregation in order to test for the robustness of the results (see 4.3). Specifically, I will present models that use political risk data for 2005 from the International Country Risk Guide (ICRG) compiled by the Political Risk Group and from the Worldwide Governance Indicators (WGI)[15] series of the World Bank. In addition to the aggregate risk score[16] of each source, I am also using a disaggregate indicator on the rule of law[17].

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[11] Gas accounting for at least 90% of a field's total hydrocarbon reserves.
[12] The Chad Cameroon project in Chad and Tiof in Mauretania.
[13] Primarily from the oil consultancies IHS Energy and Energy Intelligence, the Society of Petroleum Engineers (SPE), and from BP.
[14] Gendalo in Indonesia (Unocal 2005).
[15] I made a linear transformation of the WGI data to ensure that all values are positive by adding 2.5.
[16] Simple average of the six governance indicators in the case of the WGI data, aggregate of the twelve ICRG indicators.
[17] In the International Country Risk Guide this variable is called "Law and Order" and quantifies the strength and impartiality of the legal system and popular observance of the law. There is a large but not complete conceptual overlap with the "Rule of Law" variable from the WGI series, which measures the "extent to which agents have confidence in and abide by the rules of society, in particular the quality of contract enforcement, the police, and the courts, as well as the likelihood of crime and violence".

With respect to the dependent variable, this paper relies exclusively on cost data provided by the Goldman Sachs report as to minimize the risk of data inconsistencies. This report differentiates between F&D costs as a single category, production costs, and capex on infrastructure (for definitions see above section 2). I combine these three cost components into a single average cost variable (*cost_t)* which is provided in US$ per barrel. A table with variable descriptions and summary statistics is provided in appendix 1 and appendix 2, respectively.

4. MODELS AND INITIAL RESULTS

4.1 Exploratory models

Since the explanatory variables examined here are structured on two levels—i.e. field level and country level—an attractive option would be to use multilevel or hierarchical models (e.g. Kreft and de Leeuw 1998; Gelman and Hill 2007). The practical impediment foreclosing this option is the fact that in five cases we only have a single field per country, thereby making it impossible to accurately estimate the group level variation. I will therefore confine my analysis here to simple ordinary least squares regressions (OLS) models of the following specification

$$Y = \beta_0 + \beta_1 X_1 + ... + \beta_k X_k + \varepsilon \text{ ,} \qquad \textbf{(4-1)}$$

whereby Y is the dependent variable *costs_t* and X_1 through X_k are the dependent variables. Table 1 shows the results of four exploratory OLS regressions on *costs_t*. In model 1, k=11, as it includes all above discussed determinants of average production costs. The model contains four field specific variables, two country level variables, one interaction term (*off_pol*), and four regional dummies. *ssa* is omitted to avoid fitting a model with a complete set of dummies. Four variables—namely *api*, *ppr*, *off_pol*, and *icrg_law as well as the* two region dummies *asia* and *mena* are all significant at the

99% level. The number of observations for this model is low (67), because of the limited data availability for *wells_n*. This variable appears to be insignificant and with a very small coefficient which is why I drop it in model 2 and replicate the same regression as in model 1 but without *wells_n*. This increases the number of observations by more than a third to a total of 90 observations. The adjusted R-squared jumps from 0.669 to 0.718, *offshore* becomes significant at the 90% level, and the other variables remain significant on at least the 95% level. From this I conclude that *wells_n* should be omitted from further analysis. The only variable that remains insignificant is *hazard*.

Table 1: Exploratory models

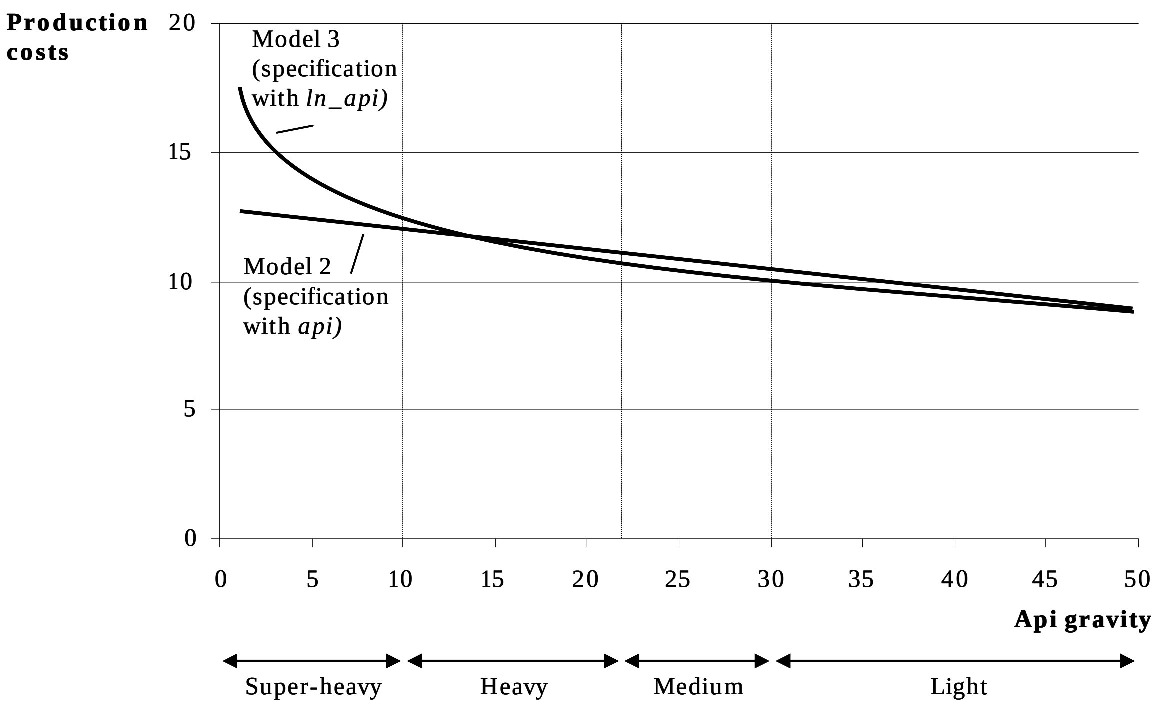
	Model 1	Model 2	Model 3
wells_n	0.000431		
	(0.00085)		
offshore	2.254	2.728	2.916*
	(1.81)	(1.67)	(1.60)
api	-0.0993***	-0.0783***	
	(0.029)	(0.028)	
hazard	0.131	0.0906	
	(0.095)	(0.096)	
ppr	77.44***	67.31***	56.41***
	(16.7)	(14.8)	(15.6)
off_pol	-1.216***	-1.309***	-1.171***
	(0.43)	(0.38)	(0.36)
west	-0.734	-0.960	-1.200*
	(0.69)	(0.68)	(0.65)
asia	-3.130***	-2.501**	-2.602***
	(0.95)	(0.95)	(0.92)
eurasia	-0.458	-1.047	-1.239
	(0.94)	(0.85)	(0.82)
mena	-4.740***	-3.620***	-3.436***
	(1.44)	(0.92)	(0.90)
icrg_law	1.679***	2.019***	1.869***
	(0.37)	(0.29)	(0.28)
ln_api			-2.253***
			(0.64)
hazard_2			0.0117*
			(0.0067)
constant	3.823*	2.685	8.437***
	(1.93)	(1.79)	(2.67)
Observations	67	90	90
R2	0.720	0.749	0.773
Adjusted R2	0.664	0.718	0.744
F-statistic	12.84	23.62	26.83
Residual sum of sq.	157.0	265.1	240.6

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Model 3 replicates model 2 with the exception that it substitutes *hazard* with its square (*hazard_2*) and *api* with its log (*ln_api*). The result is a further increase of the adjusted R-squared to 0.744. All regressors retain the same significance as in model 2, except that the regional dummy *west* and the constant now also become significant (at the 90% and 99% level, respectively). *hazard* indicates the share of a country's territory that is exposed to multiple hazards. A small value of *hazard* therefore implies that chances are high that oil fields are located outside the risk affected zone so that no cost implications arise for the oil company. Inversely, when a large portion of a national territory is exposed to natural hazards the likelihood that oil operations may be affected rises, thereby resulting in serious cost implications (Kaiser 2007). The square function seems more appropriate for capturing this relationship. Taking the log of API is motivated by the fact that the relationship between oil gravity and production costs is expected to be nonlinear. Production costs rise disproportionately when crude gravity moves from heavy to super-heavy as very different and more costly extraction techniques have to be put in place (e.g. steam-assisted gravity drainage (SAGD)), while an API increase in light crudes has a limited impact on technology and production costs (Perrodon 1998; Meyer and Attanasi 2003). This sort of relationship is better depicted by the logarithmic than the linear form as seen in figure 1, which depicts the relationship between crude gravity and average production costs for a typical onshore field in sub-Saharan Africa based on model 2 and model 3.

Heavy crudes with an API gravity of 22° or lower do not flow naturally and typically need to be diluted or heated, which increases technical complexity and costs.

Figure 1: Relationship between API gravity and average production costs



Across models 1-3, the variables retain their sign and roughly their order of magnitude. As expected, faster depletion, heavier crudes, and greater exposure to natural hazards are all associated with increasing average production costs, *offshore* appears to be more expensive than onshore, and fields in *mena* tend to have the lowest average production costs. The most interesting variable is the political risk variable *icrg_law*, which appears in all three models with a positive sign. This variable is specified in such a way that a higher score indicates lower political risk, or more precisely, better law and order, so that a positive coefficient signals higher costs in better governed countries. I will investigate this counterintuitive finding further in section 4.4.

4.2 Outliers and observations with large leverage and influence

Based on model 3, I have applied five different methods to gauge for fields whose inclusion into the dataset may overly influence the coefficient estimates. Table 2 lists all fields that have been flagged as potentially problematic by at least two of these five methods. The *resid* column indicates the studentized residuals for fields, for which this value is larger than 2 or smaller than -2. For these fields, model 3 is least capable of explaining costs. The column *leverage* indicates the leverage of fields, where this value exceeds the threshold Baum (2006) sets at $(2k+2)/N$ with k being the number or regressors, i.e. 10. The next three columns show general metrics of influence. The first such metric is Cook's D, shown for fields whose value exceeds the threshold defined as $4/N$ (Bollen and Jackman 1990). The next column displays Welsch and Kuh's (1977) DFITS for fields with values in excess of $2*(k/N)$^.5. The last column shows the number of coefficients, for which a field has been flagged by Belsley, Kuh and Welsch's (1980) DFBETA with a threshold of $2/N$^.5.

In total, 12 fields have been identified by at least two indicators and six fields even by four indicators. These formal techniques point us towards the fields we need to inspect on an observation-by-observation basis in order to decide whether the underlying data is plausible (Judson, Schmalensee and Stoker 1999). The Iranian field Soroosh Nowrooz emerges to be most suspicious observation. The Goldman Sachs report indicates unusually high production costs of $20.73 per barrel which are over 20% higher than the second most expensive field—Athabasca, an oil sands project with well known high production cost features (e.g. SAGD, upgrading). Going through various industry publications, I found no indication justifying these extraordinary cost values for Soroosh Nowrooz. On this basis, I exclude Soroosh Nowrooz from the dataset going forward.

Table 2: Metrics of residual, leverage, Cook's D, DFITS and DFBETA for influential observations

Field name	Residual	Leverage	Cook's D	Dfits	DFBeta
Salym	-2.99495	.	0.13901	-1.29745	4
Mariscal Sucre	-2.64193	.	0.085646	-1.00669	3
Holstein	-2.08426	.	0.072342	-0.91074	5
Kearl Lake	-2.95746	.	0.066201	-0.89421	2
Qasr	-2.27098	.	0.058488	-0.82294	1
Elephant	.	.	0.049686	-0.75184	2
Darkhovin	.	0.427008	.	.	2
Cerro Negro (Carabob)	.	.	0.045459	.	3
Pearl GTL	.	.	0.048881	0.745967	1
MBoundi	.	.	0.05672	0.792822	2
Ichthys	.	.	0.066739	0.869355	.
Soroosh Nowrooz	.	0.587868	0.468651	2.30953	2

Model 4 below (Table 3) retains the specifications of model 3 with the sole difference that the most suspicious observation, i.e. Soroosh Nowroz, is dropped from the sample.

4.3 Sensitivity analysis

As noted above (4.1), the political risk variable used in models 1-3 appears consistently with a positive sign. In the following, I will examine whether this counterintuitive result is driven by my choice of political risk measure and by the data source used. In a first step I will compare the more specific political risk measure used above—law and order from the ICRG dataset (*icrg_law*)—with a broader measure of political risk, namely the aggregate across all 12 risk variables in the ICRG dataset (*icrg_agg*). Model 6 therefore reruns the regression of model 4 with the only modification that *icrg_agg* is substituted for *icrg_law*. All variables retain their sign and broadly also their magnitude. Adjusted R-squared is marginally increased, and all variables except offshore are significant at least at the 90% level. Model 5 and 7 are the equivalents of model 4 and 6, respectively, with the difference that the specific and the general political risk indicator are drawn from a different source, namely the World Bank's Worldwide Governance Indicators (*wgi_law*, *wgi_ave*).

Table 3: Models with different political risk variables

	Model 4	Model 5	Model 6	Model 7
offshore	2.771*	0.368	4.103	0.835
	(1.57)	(1.06)	(2.65)	(1.18)
ln_api	-1.648**	-1.979***	-2.503***	-1.889***
	(0.70)	(0.69)	(0.69)	(0.68)
hazard_2	0.0130*	0.0205***	0.0193***	0.0223***
	(0.0067)	(0.0065)	(0.0067)	(0.0064)
ppr	38.29**	24.86	31.52*	23.92
	(18.0)	(17.8)	(18.0)	(17.5)
off_pol	-1.199***	-1.064***	-0.0882**	-1.258***
	(0.36)	(0.39)	(0.038)	(0.45)
west	-1.012	-1.720**	-2.171***	-1.897**
	(0.65)	(0.73)	(0.81)	(0.74)
asia	-2.661***	-3.206***	-3.594***	-3.209***
	(0.90)	(0.90)	(1.03)	(0.89)
eurasia	-1.641*	-1.415*	-2.335**	-1.504*
	(0.83)	(0.80)	(0.92)	(0.78)
mena	-3.819***	-3.898***	-3.902***	-3.481***
	(0.91)	(0.85)	(0.94)	(0.82)
icrg_law	1.885***			
	(0.28)			
wgi_law		1.997***		
		(0.28)		
icrg_agg			0.184***	
			(0.027)	
wgi_ave				2.412***
				(0.31)
constant	7.394***	12.10***	6.051*	10.82***
	(2.68)	(2.50)	(3.14)	(2.56)
Observations	89	89	89	89
R2	0.750	0.771	0.754	0.783
Adjusted R2	0.718	0.742	0.722	0.755
F-statistic	23.38	26.27	23.86	28.08
Residual sum of sq.	229.6	210.1	226.1	199.5

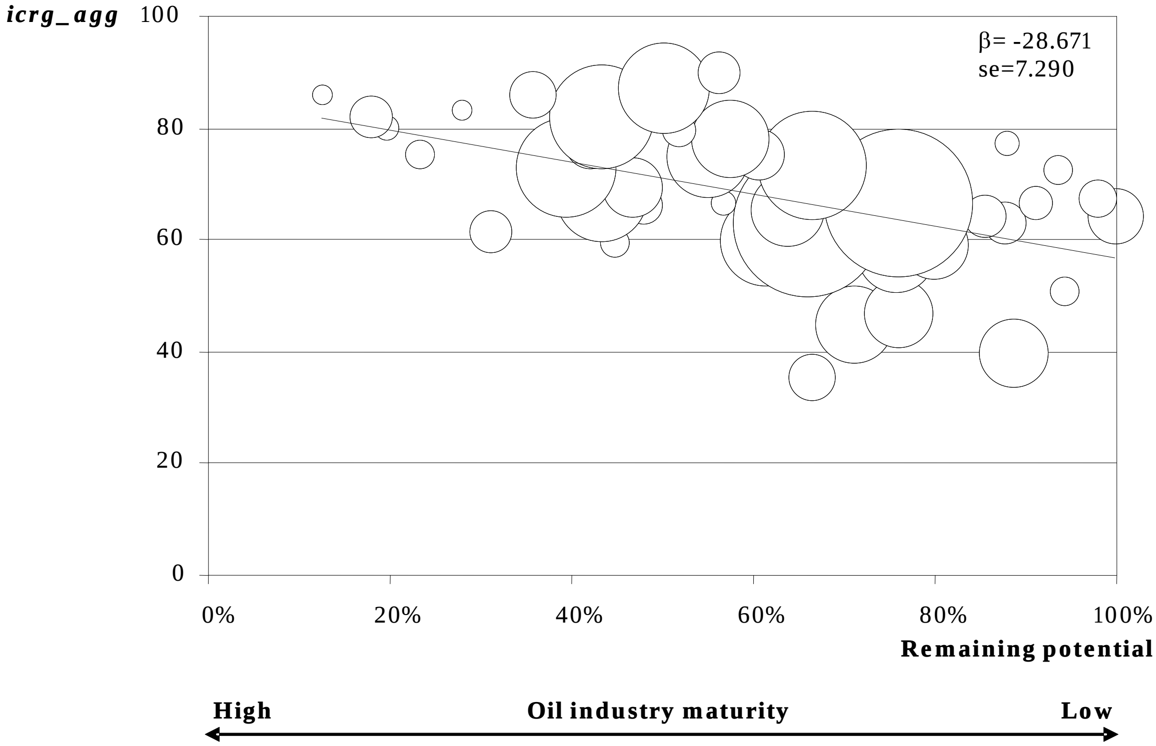
Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Again, there is relatively little difference across these models, leading me to conclude that the positive sign for political risk found in models 1-7 may not be spurious. A possible interpretation of the apparent positive correlation between the rule of law and average production costs may be found in the historic selection bias in favor of low risk countries. From day one of the modern petroleum industry, international oil companies have favored fields low risk countries over those in high risk countries (Lax 1983), with the consequence that well governed countries tend to have a smaller fraction of their oil endowment left for future exploration and development than do high risk countries. The scatter plot below in figure 2 depicts this inverse relationship between our political risk variable and the share of remaining oil potentials over total oil potentials (BGR 2006)[18]. It seems therefore plausible to assume that political risk *per se* does not lead to a reduction in production costs, but rather indicates the endogeneity of the historic project selection process replicated by the Goldman Sachs dataset.

Across models 4 to 7, the interaction term *off_pol* appears with a negative sign. This suggests that the increase in costs with an increase in the ICRG or WGI risk scores is less pronounced in offshore fields than in onshore fields. This finding is in line with the endogeneity argument presented above. As onshore fields started to be developed earlier than offshore fields, more of the low cost fields in low risk countries have been depleted onshore than offshore.

[18] weighted by remaining oil potentials

Figure 2: Industry maturity and political risk



A second element of the explanatory models presented above presents itself as an obvious candidate to be subjected to a sensitivity analysis: the regional dummies. Models 1-7 all differentiate between a total of five regions—*west, asia, eurasia, mena, ssa* (omitted). The specification of *mena* as a separate category was motivated by the conventional wisdom that fields in this region tend to be less costly than fields in other world regions (e.g. Adelman and Shahi 1989). In contrast, the categorization of the other four regions was less driven by theoretical considerations than by the practical need to ensure that all regions comprise at least three countries. To test whether my regional grouping has an undue impact on the estimation results, I rerun models 4-8 with the sole modification being a binary regional categorization differentiating between countries in the Middle East and North Africa (*mena)* and countries outside that region (*non-mena,* omitted). Table 4 shows that this recategorization does not alter the general insights gained from the models with the original regional grouping. The coefficients retain their sign and broadly their order of magnitude. The significance level of the individual variables varies slightly, with only model 11 showing all variables to be significant. The most important difference between these binary region models (models 8-11) and the original models (models 4-7) is that the values of R-squared are slightly lower in the former set than in the latter. This is not surprising as the regional dummies were jointly significant in the models with the original regional categorization[19]. Consequently, we will inevitably lose explanatory power by collapsing four regions into a single *non_mena* variable.

[19] The joint test for model 4 gives a p-value is 0.0013, meaning that the null hypothesis that all dummies are zero can be rejected with 99% confidence.

Table 4: Models with binary regional categorization

	Model 8	Model 9	Model 10	Model 11
offshore	4.335***	1.613	8.787***	2.491**
	(1.51)	(1.01)	(2.40)	(1.10)
ln_api	-1.843***	-1.618***	-2.269***	-1.446***
	(0.54)	(0.53)	(0.52)	(0.53)
hazard_2	0.00962	0.0148**	0.0146**	0.0165**
	(0.0065)	(0.0064)	(0.0066)	(0.0063)
ppr	46.04***	39.00**	42.74**	39.27**
	(16.9)	(16.3)	(16.9)	(16.0)
off_pol	-1.582***	-1.660***	-0.157***	-2.024***
	(0.34)	(0.35)	(0.033)	(0.40)
mena	-2.497***	-2.690***	-2.086**	-2.289***
	(0.79)	(0.77)	(0.79)	(0.75)
icrg_law	1.851***			
	(0.29)			
wgi_law		1.984***		
		(0.29)		
icrg_agg			0.180***	
			(0.029)	
wgi_ave				2.403***
				(0.33)
Constant	6.685***	9.160***	3.258	7.502***
	(2.36)	(2.00)	(2.89)	(2.08)
Observations	89	89	89	89
R2	0.721	0.733	0.713	0.745
Adjusted R2	0.697	0.710	0.688	0.723
F-statistic	29.89	31.78	28.78	33.76
Residual sum of sq.	256.2	245.0	263.2	234.3

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

4.4 Heteroskedasticity and multicollinearity

In a final step, I will examine in more detail the quality of model 4 by testing first for heteroskedasticity and second for multicollinearity.

The p-value for White's test is 0.1593 which indicates the null-hypothesis for homoskedasticity cannot be rejected. This is confirmed by the Beusch-Pagan/Cook-Weisberg test, which yields an even higher p-value of 0.5257. I also tested the specification of the model with Ramsey's omitted-variable regression specification error test and with the link test. The p-value for RESET is 0.5435, and the p-value for the link test's square variable is 0.218, both of which indicate that the model is specified correctly.

Multicollinearity does not appear to be a problem in model 4 either. With a condition index of 9.7178 it remains well below the threshold of 30 that is commonly referred to as indicating harmful collinearity (Kennedy 2003).

5. FINAL RESULTS AND CONLUDING REMARKS

Most of the models presented above explain more than 70% of the variance in the average unit production costs of recently developed oil fields. This explanatory power is impressive for models that rely exclusively on non-proprietary cost data and on high level explanatory variables.

The estimates produced in this paper provide an empirical underpinning for a number of technical cost factors that are generally considered to be relevant but for which barely any cross-national field level studies have been carried out. All models confirm the hypothesis that average production costs are higher offshore than onshore. Model 4 suggests that average production costs in offshore fields are *ceteris paribus* US$2.77 per barrel higher than onshore production. As offshore discoveries are expected to account for close to half of the total amount of reserves that will be added by 2030—and the lion share of non-OPEC reserve expansion (IEA 2003, 109)—the higher production costs of offshore fields will sustain an increase in structural costs over the long run. This upward push is reinforced by the negative relationship between crude gravity and average production costs confirmed by all models on a significance level of at least 95%. The marked increase in average production costs that every one degree drop in API gravity entails in the heavy and extra heavy oil spectrum will be of growing importance when the share of non-conventional oil expands from currently 2.1 % to 8.3% of total supply by 2030 (IEA 2004, 114). The climate change related increase in more extreme weather events and related natural disasters will further rise the floor of structurally determined production costs, as the natural hazard variable (*hazard_2*) is confirmed to have a significant positive impact on average production costs. Also confirming conventional wisdom is the positive coefficient found for *ppr* which suggests increasing average production costs with higher depletion rates. Specifically, model 4 indicates that average production costs increase by US$0.38 per barrel with every 1% increase in a field's depletion rate. With the growing average age of fields and the related drop in reserve expansion (IEA 2005, 64) this factor will continue to gain in prominence.

The model also confirms at the 99% significance level the conventional assumption that oil fields in the Middle East and in North Africa offer the lowest average production costs in the world. Specifically, model 4 quantifies the cost difference vis-à-vis production in sub-Saharan Africa to be more than US$3.7 per barrel. The growing share of oil from Middle Eastern OPEC countries from a quarter to more than 40% by 2030 (IEA 2004, 106) will slightly mitigate the cost increase caused by the factors discussed above.

The most surprising finding of this paper is the counterintuitive positive relationship between production costs and political risk confirmed by all models at a 99% significance level. Model 4 suggests that with every increase in the ICRG law and order score (*icrg_law*) average production costs rise by almost US$1.9 per barrel. As discussed in more detail above, the most plausible reason of this unexpected result lies in the endogeneity of the historic sequencing of new oil projects with the consequence that the oil sector in low risk countries tends to be more mature than in high risk countries. This endogeneity problem is less pronounced in offshore fields than in onshore fields as suggested by the negative sign of the *off_pol* interaction term.

Endogeneity affects not only the coefficient estimate of the political risk variable but also the overall costs predicted by the model. Since the Goldman Sachs report intentionally covers only recent oil and gas projects that are deemed particularly profitable, it represents a case of endogenous sample selection that introduces a downward bias in OLS in estimating the population model. In other words, average production costs for the universe of recent petroleum projects are likely to be higher than the costs factors estimated in this paper would predict. However, this bias does not nullify the insights this paper can offer. The models presented here still help us better understand the order of magnitude in which the ongoing push into fields with heavy crudes, and/or located offshore and in high risk countries will affect the floor of structural cost trends.

In order to reach a comprehensive model of cost trends future research can build upon the models of structural cost components presented here and combine them with projections of these factors' development and with models that capture the cyclical variability of the costs of input factors and changes in petroleum fiscal regimes. By quantifying the technically determined cost impact of today's move beyond easy oil this study makes a first contribution to enhance our understanding of the cost implications of this irreversible trend.

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7. APPENDICES

7.1 Appendix 1

Variable name	Variable description
costs_t	Total average production costs, including finding, development, and lifting costs plus capital expenditures on infrastructure (in US$ per barrel)
wells_n	Number of wells per field
api	API gravity (in degrees)
ppr	Annual production per reserves (in years)
hazard	Share of a country's territory exposed to multiple natural hazards (in %)
icrg_law	Law and order score from International Country Risk Guide
icrg_agg	Average score from International Country Risk Guide
wgi_law	Rule of law score from Worldwide Governance Indicators
wgi_ave	Average score from Worldwide Governance Indicators
offshore	= 1 if located offshore, 0 otherwise
mena	= 1 if located in the Middle East or North Africa, 0 otherwise
west	= 1 if located in Latin America or North America, 0 otherwise
eurasia	= 1 if located in Europe or the Former Soviet Union, 0 otherwise
asia	= 1 if located in East or South Asia, 0 otherwise
ssa	= 1 if located in sub-Saharan Africa, 0 otherwise

7.2 Appendix 2

Variable	Mean	Standard deviation	Minimum	Maximum
costs_t	9.02743	3.447273	3.375	20.7897
wells_n	104.672	301.6977	0	2000
offshore	0.67778	0.469946	0	1
api	28.8044	11.58655	7.5	48.9
ln_api	3.24169	0.546945	2.014903	3.88978
hazard	1.44111	3.42807	0	17.1
hazard_2	13.6979	53.89628	0	292.41
ppr	0.04716	0.024408	0.020833	0.2
icrg_law	3.79028	1.425732	1.666667	6
wgi_law	2.3864	1.264922	1.03716	4.44993
icrg_agg	66.9699	14.06795	44.20834	88.375
wgi_ave	2.42079	1.087174	1.274998	4.23276