UNIVERSITY OF AMSTERDAM

MASTER'S THESIS

To Drill Or Not To Drill?

How Corruption Affects The Extraction of Natural Resources

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Abstract

The sustainable management of non-renewable resources is crucial for long-term development. Previous, mostly theoretical, evidence suggests that extraction levels are generally over-extracted, for which corruption is a common explanation. However, as some argue for the opposite effect, whether this distortion leads to resource owners extracting more or less than optimal remains contested. Additionally, much of the empirical evidence attempting to study the causal effect of corruption on natural resource extraction suffers from endogeneity problems. This thesis addresses this issue, presenting an empirical analysis leveraging a plausibly exogenous variation in corruption with a shift-share analysis. Specifically, the analysis uses a temporally invariant corruption proxy (Ethnic Fractionalization) and interacts it with an exogenous variation in world oil prices. The approach estimates how time-invariant corruption affects the number of oil- and gas wells drilled following exogenous resource price changes. The sample comprises 28 oil-producing Indonesian regencies (municipalities) that have drilled production wells between 2002 and 2018. Because spatial spillovers are commonplace within studies of this nature, I employ a spatial autoregressive model (SAR). The analysis shows that corruption leads to over-extraction. For instance, a one standard deviation increase in oil prices causes a 1 percentage point more ethnically fractionalized regency to drill 0.04 new wells. I also estimate the impact using audit scores—a proxy of financial corruption— and find no evidence of an effect. While there is clear evidence of corruption driving over-extraction, the type of corruption appears to matter. Grabbing behavior stemming from political competition is important, whereas financial manipulation is unrelated.

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1 Introduction

Exploiting non-renewable natural resources optimally has crucial implications for a country's development, and the existence of such an optimum has become a key area of research in natural resource economics. A seminal contribution by Hotelling (1931) prescribes that, in optimality, the price of a non-renewable resource will rise at the interest rate and resource owners adjust their extraction volumes in each period accordingly. Although their theoretically optimal extraction path (the rate at which the non-renewable resource is depleted) is well understood, the resource owner's actual extraction path differs significantly (e.g Bohn and Deacon 2000; Farzin 1984; Krautkraemer 1998; Lasserre 1982; Pindyck 1978; Slade 1982). A large body of literature has suggested the presence of economic and political distortions, even under modern interpretations of the Hotelling rule, cause resource owners to deviate from the predicted path (e.g. Anderson et al. 2018; Karp 2017; Perman et al. 2011; Stroebel and Benthem 2013). The focus of this paper concerns one such distortion, namely the effect of government corruption on the extraction rates of non-renewable natural resources.

Theoretically, the distortive effects of corruption could alter the decisions of the resource owners, both the government and the operating firms. For governments, corruption will induce rent-seeking behavior amongst politicians and bureaucrats because electoral cycles cause corrupt politicians to maximize their gain over a limited term. In other words, they will optimize extraction rates solely over their time in office, while disregarding what is optimal for society in the long run (Robinson et al. 2006).[1] Additionally, the firms operating in places governed by corrupt politicians and bureaucrats will face higher operation risks. From their perspective, it is always possible that a profit-maximizing politician finds it more beneficial to renege on an ongoing contract at any time. Thus, this fear of expropriation leads the operating firms to become short-sighted, wanting to extract more today in anticipation of losing the rights to exploit the resource in the future. (Kronenberg 2008; Lasserre 1982). Both channels may explain over-extraction: a key decision-maker in the extraction process turns myopic and over-extracts in current periods. Because a devaluing of the resource causes this over-extraction, I denote this effect as the discounting effect.

In contrast, some theoretical papers point to the opposite effect, suggesting corruption lowers extraction rates (Bohn and Deacon 2000; Farzin 1984). In this scenario, the same short-sightedness caused by corruption in the case of the discounting effect also reduces incentives for the resource owner to invest in the future. If the resource owner fears expropriation, any investment made today has a small chance of being wasted. If a given resource exploitation project is sufficiently capital-intensive and requires a bulk of the capital to be expended upfront (in the case of most mined resources), a resource owner might decide not to enter. These projects might have been deemed commercially viable were it not for the investment disincentives. Summing up all these rejected projects result in a flatter than optimal extraction path (under-extraction). Paradoxically, more corrupt institutions would unintentionally engender more sustainable extraction. This I denote as the disinvestment effect.

For the resource owner, these counteracting effects relate to two consecutive decisions in the extraction process. Initially, the resource owner needs to decide whether to enter an exploitation project in the first place. At this stage, the disinvestment effect would appear as corruption will deter resource owners from providing the necessary capital investments to initiate the project. In the second stage, when resource owners have decided to enter the project, the question becomes: how much to extract? Now, the discounting effect would appear. The upfront investment has already been made and resource owners are committed to the project, but corruption could reduce their certainty about future payoffs. On an aggregate level, with several such projects existing simultaneously, observing whether the resource is over- or under-extracted should reveal which effect dominates. Because it remains unclear theoretically which dominates, the question becomes empirical.

[1] Robinson et al. (2006) show theoretically that this finding also holds for dictatorships. The rent-seeking politician always faces uncertainty about her likelihood of staying in power.

Although there is a wide literature on the effects of corruption on non-renewable natural resources, these are typically studied in a resource curse context (Acemoglu et al. 2004; Atkinson and Hamilton 2003; Caselli and Michaels 2013; Sachs and Warner 2001). Such studies do not study the behavior directly, but consider over-extraction as a potential explanation for resource curse mechanisms. Only two cross-country studies find correlations between the risk of expropriation and extraction. Constructing an ownership risk index, Bohn and Deacon (2000) find cross-country correlations to suggest that riskier countries tend to extract less petroleum. This implies that the disinvestment effect dominates for non-renewables like oil and gas. Olsen (2013) find similar results for minerals. However, the causal direction of these estimates is unclear. Their ownership risk can indeed cause under-extraction. However, extraction rates simultaneously provide a lucrative source of revenue for governments which in turn could affect the ownership risk. Because corruption, much like this ownership index, faces this reverse causality concern, a crucial aspect of any empirical paper attempting to estimate the causal effects of corruption on extraction rates (or vice-versa) will be to disentangle the two causal directions properly. I isolate the effect of corruption on extraction rates through an alternative shift-share estimation method (Bartik 1991).

Specifically, this paper investigates whether corruption leads to higher drilling activity for oil and gas development wells within Indonesian regencies (municipalities). Following a nation-wide decentralization policy implemented in November 2001, regencies gained greater autonomy over their jurisdiction's oil and gas resources. This had two important implications: 1) regencies now received a share of the oil and gas revenues, providing an economic incentive for drilling, and 2) they became the first point of contact with which oil companies needed to consult to attain the rights. Together, the first policy change incentivizes regencies to control the extraction rates within their jurisdiction and the second provides them the power to do so. Depending on whether the disinvestment or discounting effect dominates, one should expect extraction rates in more corrupt regencies to be higher or lower.

To show that this effect is indeed causal, that corruption causes more drilling, I operationalize corruption using a measure of the ethnic fractionalization within each regency provided by Arifin et al. (2015). This proxy has proven to be a good indicator in previous studies (Alesina et al. 2003; Dincer 2008), and, crucially for my identification strategy, I argue its properties make it nearly time-invariant. Without any variation from my corruption proxy, I interact with it with oil prices providing the exogenous variation. World oil prices are exogenous simply because Indonesian regencies are so small that they are price takers. Further, I run a similar regression using regional gas prices which should be similarly exogenous.

This study employs a novel geospatial dataset on oil and gas drillings reported by the Directorate General of Oil (ESDM 2020) to identify the number of development wells drilled per regency between 2002 and 2018. Out of a panel of 514 regencies, I identify 28 as oil producers (see Appendix 10.2) resulting in 476 regency-year observations. Furthermore, I apply a two-way fixed-effects Spatial Autoregression (SAR) model, to account for potential spatial spillovers of many of the measures used in within-country estimations.

The findings unequivocally support the discounting effect, both for oil and gas. A 1 standard deviation increase in oil prices causes a 1 percentage point more ethnically fractionalized regency to drill 0.04 more wells. A single successful well will produce several thousand barrels of oil over its lifetime, so even such a seemingly small effect might lead to sizeable differences in the long run. In addition, to better understand the nature of the corruption driving these effects, I ran the same test using auditing scores provided by the Audit Board of Indonesia (BPK) as an alternative proxy. Audit score measure the financial compliance of regencies. The less compliant, I argue, the more plausibly corrupt the regency government is. Unlike the regression using ethnic fractionalization, I find a statistically insignificant effect for the corruption-oil interaction when using this proxy. Auditing scores capture different corrupt behaviors, which might explain the lack of significance. It is plausible that only some corrupt behaviors drive the observed effects. Lastly, the results show that both corruption measures exhibit spatial spillovers. I find that while there is no evidence of a direct spillover effect from extraction rates themselves, through corruption, more drilling might still occur. If one regency is corrupt nearby oil-producing regencies are more likely to over-extract.

This study offers three notable contributions to the literature. To my knowledge, this study provides a first attempt at properly identifying the causal effect of corruption on extraction rates of non-renewable resources. Previous studies have attempted this for renewable resources (Balboni et al. 2021; Barbier et al. 2005), for exploration activities (Cust and Harding 2020) or other measures of good governance (Kemal and Lange 2018). Additionally, using a within-country study helps to identify this causal effect more accurately. Therefore, this thesis complements the recent shift in the literature towards within-country studies for greater disaggregation of economic responses and a cleaner empirical analysis (Cust and Poelhekke 2015). As such, the finding in this study is novel in its contribution to a longstanding theoretical problem.

Secondly, little attention has been paid to the potential for spillover of extraction behavior. While I find no evidence of a direct spillover, variables from proximate areas appear to affect it. For example, my results show a significant risk for both corruption measures used in this study to spread across borders. This is nothing new as it aligns with the predictions following the existing literature on corruption (Donfouet et al. 2018; Khodapanah et al. 2022). However, going one step further, the findings show that financial corruption (as measured by audit scores), beyond having a direct spillover effect, may also induce over-extraction of nearby non-corrupt areas. Hence, this study provides new evidence on the intricate spatial linkages between corruption and unsustainable resource management. It is the hope that in doing so, governments will better understand how corruption interacts spatially with other deleterious behaviors and enact better policy responses accordingly.

Lastly, the study attempts to contribute to the literature by using an alternative measure of extraction rate that more appropriately represents the optimization problem of the resource owner. The current literature has primarily focused on the production-to-reserve ratio rather than drilling (Bohn and Deacon 2000; Kemal and Lange 2018; Olsen 2013) to account for the different speeds with which resource owners extract. Anderson et al. (2018) and Mason and Veld (2013), amongst others, show this ratio has remained roughly constant over time, even in the face of large price variations. In particular, fluid dynamics predicts that production from a well declines at an exogenous rate determined by geological parameters (known as Darcy's Law). Hence, the resource owner can only control the number of deposits to open up for extraction. I leverage this insight to shift the empirical problem away from, in the words of Anderson et al. (2018), a simple "cake-eating" towards a more realistic "keg-tapping" problem.

The sections are as follows: in Section 2, I delve more into the theoretical predictions of the effects and the existing literature. Section 3 discusses the identification strategy and Section 4 discusses the data. In Section 5 I present the econometric model. Section 6 provides the results, while Section 7 assesses the robustness of the findings. I include a brief discussion of the study in Section 8 before adding concluding remarks in Section 9.

2 Literature Review

2.1 Theoretical predictions of the Hotelling rule

Theoretically, an owner of a non-renewable resource wishes to maximize her profit in each period until it is depleted.[2] For simplicity, I assume that profits are determined by the amount of the resource extracted, the market price, and the marginal extraction costs in the current period. The resource owner's valuation of her resource in present terms (V) is thus a function of the sum

[2] In my study, ownership is divided threefold between the national government, the regency government, and the oil company.

of discounted future profits until the time of depletion. Mathematically, the expression becomes:

$$V = \sum_{t=0}^{T} \frac{\Pi(R_t)}{(1+\rho)^t} \tag{1}$$

where the profit function $\Pi(R_t)$ is defined as:

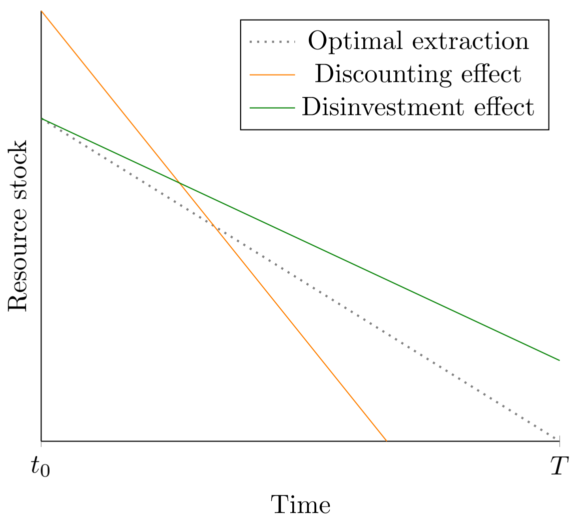
$$\Pi(R_t) = (P_t - mc_t)R_t \tag{2}$$

T is the time of depletion, R_t is the amount of the resource extracted in period t, ρ indicates the resource owner's discount rate (that is, her preference for present returns), P_t is the market price of the resource, and mc_t is the marginal extraction cost. Using these expressions, I can find the optimal extraction rate assuming an inverse oil-demand function (see Appendix 10.1):

$$R_t = \frac{\rho(T-t)}{a} \tag{3}$$

where a is a parameter capturing the sensitivity of prices to the extraction rate. Assuming that ρ and a are constant, the resource thus follows a linear path towards depletion (see Figure 1).

Figure 1: The three extraction paths



Note: Extraction rate is the slope of the respective extraction paths

These predictions are far from novel. Hotelling (1931) was the first to present this relationship. The literature has since put this prediction into question, however (Anderson et al. 2018; Krautkraemer 1998; Kronenberg 2008; Lee et al. 2006). Resource owners do not reach this optimal extraction path due to various distortive mechanisms.[3] Although most such distortions indirectly affect extraction rates by impacting marginal profits, there exists another set of institutional factors directly affecting resource owners' behavioral responses, of which corruption is one. Here, assuming the right over the resource is not nationalized, distortions from corruption can occur both from a company and the government (Al-Kasim et al. 2013). This will happen at the firm level by intensifying drilling efforts within its concession and reducing its capital investment into new ones. At the government level, this will occur through the overprovision of drilling rights.[4]

[3]The literature lists at least 3 principal sources of distortion: variable extraction costs, discovery shocks, and monopoly power over the market (Kronenberg 2008).

[4]This study only evaluates the combined discounting effect of the resource owner and the government but encourages future research to isolate it at firm and government levels.

2.1.1 The Discounting Effect

At the firm level, those who operate under corrupt governments risk losing their rights over their designated drilling area every period. During production, the more corrupt the government the less secure the firms consider their property right over the resource. Mathematically, this becomes more apparent. Assuming two possible outcomes in each period: (1) the government expropriates the resource with probability μ (profits are indefinitely lost) or (2), ownership is retained with probability $1 - \mu$, the resource owner's maximization problem of the present net profit value of the resource is as follows:

$$\max_{\{R_t\}} V = \sum_{t=0}^{T} \Pi(R_t) \left(\frac{1-\mu}{1+\rho}\right)^t \tag{4}$$

$$s.t. \quad S_{t+1} = S_t - R_t \tag{5}$$

Here, μ describes the hazard risk, the likelihood of the corrupt government reneging on an agreement causing a loss of ownership over the non-renewable resource. R_t is the volume extracted and S_t is the remaining resource stock in period t. Using the same method as before, the new extraction path takes on the following form (see Appendix 10.1 for deduction):

$$R_t = \frac{(\mu + \rho)(T - t)}{a} \tag{6}$$

Comparing (3) with (6), it becomes clear that introducing this uncertainty caused by corruption raises the extraction rate (as illustrated by Figure 1) of a firm within their awarded drilling area.

A key question is why a corrupt government would want to renege on an agreement in the first place. As Stroebel and Benthem (2013) discuss, expropriations result from a risk-averse government reneging on a contract that provides valuable insurance at low oil prices. Importantly, they stress the informational asymmetry between the operating firm and the government surrounding the costs the latter incurs by expropriating. In this sense, the business economics literature has already shown how firms operating in highly corrupt environments face greater informational asymmetry (Pantzalis et al. 2008; Tsai et al. 2021). The link between corruption and hazard risk should, thus, be clear: the more corrupt, the more asymmetry and the greater uncertainty (μ) the firm faces.[5] On the government side, corruption will naturally distort the political incentives of the administration. The priorities of a rent-seeking politician or bureaucrat will shift away from long-term social goals to personal gains over the limited time they remain in office. This would introduce a discount rate $\rho*$ higher than the socially optimal, ρ. Substituting this into equation (3), I naturally get a higher-than-optimal extraction rate. This over-discounting of the future could also cause inefficient planning (Robinson et al. 2006) and weaken its negotiating power with resource extractors (Al-Kasim et al. 2013), both of which will further aggravate the extraction distortions.

2.1.2 The Disinvestment Effect

There is, however, another mechanism at play. Within the business economics literature, the evidence for corruption reducing capital investment is well-documented (Cieślik and Goczek 2018; Mo 2001; O'Toole and Tarp 2014). This also relates to non-renewable resource extraction: corruption will introduce uncertainty for the resource extractor as described above, but now her capital investments into future periods are also at risk.

$$K_{t+1} = (1 - \mu) I_t + (1 - \delta) K_t \tag{7}$$

Where K_t represents the capital stock and, I_t is the capital investment. In cases where a resource extraction process is particularly capital-intensive, the extractor faces a different total

[5] Furthermore, in the case of oil and gas in Indonesia, the lack of coordination between the Ministry of Finance, ESDM, and PERTAMINA has created additional uncertainty for IOCs on expiring PSC contracts (Roach and Dunstan 2018).

cost function:

$$TC = C_0 + \sum_{t=1}^{T} mc_t Q_t(R_t,\ K_t) \tag{8}$$

Where C_0 represents the upfront capital investments before exploitation can begin (e.g. seismic testing, obtaining the permits, developing the machinery). This will depend on both geological and institutional factors. Q_t is a production function where the two input factors are complementary.[6] The running marginal costs, mc_t, will naturally increase with the production volumes. The representative resource extractor's decision of whether to enter a resource exploitation project then becomes a simple cost-benefit analysis:

$$\Pi = \begin{Bmatrix} \left[\sum_{t=1}^{T} (P_t - mc_t)\, Q_t(R_t,\ K_t)\right] - \ C_0 & if\ V > 0 \\ 0 & if\ V \leq 0 \end{Bmatrix} \tag{9}$$

A slowing down of capital growth due to corruption's stifling of investments will lower production in each period and flatten the extraction path (see Figure 1). Considering that the upfront costs (C_0) are sizeable enough, this reduction could shift the value of some initially commercially viable resource deposits ($V > 0$) towards becoming unprofitable ($V \leq 0$). As a result, more of the government's total resource stock will be left untapped causing aggregate extraction rates to decrease. Importantly, this effect depends on the capital intensity of the resource extraction process.[7] If the capital intensity is relatively low, it will only marginally impact production and the upfront investment costs will be small, lowering the barriers to entry.

The resource extractor, therefore, faces two consecutive decision-making processes: first, whether to enter a drilling project at all given the reduced incentives for investments and, after entering, how much to discount the future given the uncertainty of operating under a corrupt government. This brings me to the two opposing hypotheses in this analysis:

> ***H1a**: The discounting effect dominates and an increase in corruption should cause extraction rates to increase.*
>
> ***H1b**: The disinvestment effect dominates and an increase in corruption should cause extraction rates to decrease.*

2.2 Findings from the literature

In this section, I touch upon the relevant literature to provide preliminary evidence for the two hypotheses. From here, I assign oil (and natural gas) to the unspecified non-renewable resource discussed above.[8]

Firstly, the potential reserve causality concerns of studying corruption and resource extraction are important to address. Much research has been devoted to showing how the effects of oil and gas production (and revenues) can deepen corruption (Atkinson and Hamilton 2003; Sachs and Warner 2001). Furthermore, studies suggest that such revenues tend to be increasingly reinvested back in the oil and gas sector, rather than allocated to public goods (Al-Kasim et al. 2013; Kolstad and Søreide 2009; O'Higgins 2006). This cycle which increases incentives for rent-seeking, illustrates the simultaneous effect of corruption on extraction and extraction (and by extension oil revenues) on corruption. Crucially, research must properly isolate the above two-way effects to make clear causal inferences.

More attention has been paid to disentangling these two causal effects in the literature on sustainable forest management (Barbier et al. 2005; Galinato and Galinato 2013; Sommer 2017).

[6] Here, I assume the output elasticity of labor to be significantly small relative to capital.

[7] For a more in-depth discussion of the disinvestment effect and how it relates to capital intensity, see Bohn and Deacon (2000), Farzin (1984), and Lasserre (1982). They also suggest that this disinvestment effect dominates over the discounting effect if the resource extracted is highly capital-intensive, as is the case for oil and gas, which gives more credence to the alternative hypothesis.

[8] Because natural gas is usually extracted simultaneously, I assume its theoretical foundations are similar.

Here, findings consistently point to a significant positive impact of corruption on over-extraction (in other words, deforestation), particularly through illegal logging. Additionally, given Indonesia's status as one of the most biodiverse countries in the world, there has been no shortage of research on this effect within the focus area of my study neither (Balboni et al. 2021; Eldeeb et al. 2015; Pachmann 2022). Although the discounting effect seems to dominate in such industries, it shares little in common with oil and natural gas. Timber has a (slow) renewability rate for once, significantly altering the resource exploiters' optimization problem. Secondly, forests possess a range of benefits beyond the value of the timber itself, such as recreational use, carbon sinks, and flood prevention. Lastly, timber constitutes a labor-intensive resource. Unlike the high upfront capital investment costs concerning oil and gas extraction, logging requires relatively little to get started. These low barriers to entry combined with the low willingness or ability of corrupt governments to prevent the illegal exploitation of forests, further aggravates the over-extraction. This is not an issue shared by the oil and gas problem as the resource is naturally much more excludable.

This point is crucially noted by Bohn and Deacon (2000) who develop a model for optimal extraction with endogenous capital investments. They argue that whether the risk parameter leads to the discounting or the disinvestment effect dominating depends on the capital intensity of the resource extraction process. Their cross-country estimations support this prediction: the discounting effect dominates in the case of timber production, while the disinvestment effect dominates in oil production. These findings are corroborated by Cust and Harding (2020) for the search and discovery of oil and Olsen (2013) for iron and coal exploitation. Whether this also applies within countries is a central motivation of this study.

At the same time, some research suggests that the discounting effect persists for capital-intensive resources such as oil and gas. Robinson et al. (2006) develop a political model considering a rent-seeking incumbent's incentives. The model balances the incumbent's profit-maximizing resource rents with the likelihood of losing ownership over them through losing power.[9] Because rent-seeking politicians only care about the value of the non-renewable resource as long as they stay in power, introducing political incentives into the model shifts their preference towards the present, leading to over-extraction. Kemal and Lange (2018) provide potential support for the discounting effect by studying an exogenous change in an Indonesian oil governance system (from Pertamina to BP Migas), during the 2001 decentralization policy (see Section 3.1). Using a difference-in-difference method, they show that nationwide extraction rates dropped roughly 40 percent after the policy change. While directly tied to corruption, they argue that the previous oil governance system was less transparent, which raised uncertainty amongst Independent Oil Companies (IOCs) and increased the extraction rate.

In conclusion, there is evidence to suggest but no evidence to confirm that either effect can potentially dominate. Likely, both effects exist simultaneously, but providing decisive proof for either of the two hypotheses thus far has been challenging. Therefore, the following section presents the identification to estimate the effects of the twin hypotheses.

3 Identification strategy

The aim is to study the effect of corruption on non-renewable resource extraction, specifically oil and natural gas within Indonesia. Aside from being difficult to measure directly, the challenge in identifying corruption is that extracting natural resources may also exacerbate it. There is reverse causality leading to endogeneity. Accordingly, my identification strategy aims to find a causal effect from a proxy of corruption on natural resources.

I use the logic of shift-share instruments in my identification (Bartik 1991) by constructing a variable I claim has exogenous temporal variation. In my baseline regression, I create the variable by taking a constant corruption level (share) and multiplying it by the world oil price (shift).

[9] This could happen through democratic elections or through getting ousted in the case of dictatorships.

Accordingly, the variable shows the relative magnitude of corruption in a regency given a certain price level. For example, if world oil prices rise, the variable increases more for more corrupt regencies than those less corrupt. This variation, however, is entirely caused by the change in world oil prices. In my sample, world oil prices are exogenous simply because Indonesian regencies are so small that they are price takers. As such, the main independent variable is an interaction term that changes based on exogenous oil price fluctuation moderated by time-invariant corruption levels.

This plausibly exogenous independent variable is regressed on the dependent variable, the number of oil and gas wells drilled. Oil extraction is proportional to the number of active wells. However, not all well drillings lead to active, extractive wells. Therefore, I am interested in drilling, since they convey the intention to extract, capturing the behavior that should follow the predicted discounting or disinvestment effect. Furthermore, the number of wells cannot explain the change in world prices captured by the independent variable, and there is no reverse causality. The relevant considerations that enable my empirical test will be discussed in this section.

3.1 The policy change

An important policy change in 2001 is what enables the identification of drilling activity at the regency level. With the demise of Suharto in the late 1990s, decentralization policies seeking to reduce the instabilities caused by the previous authoritarian regime and promote regional development led to regency governments gaining greater levels of autonomy. For oil and gas, the biggest policy change came in the form of *Law No. 22 of 2001*, which stripped Pertamina of its status as a national oil company and transferred authority over the management of the product sharing contracts (PCSs) to BP Migas (now SKK Migas), a separate regulatory entity.[10] [11] Importantly, the law stipulates that IOCs must secure recommendations from the regency government before entering PSC negotiations with BP Migas.[12] This means that the regency governments control the extraction intensity of oil and gas within their jurisdiction, causing corruption to become endogenous at the regency level.

The second crucial element of this policy is the revenue sharing. Under *Law No. 22*, revenues from the PSCs are divided between the central government, regencies, and IOCs. Table 1 shows the new allocation of the oil and gas revenues. While the decision-making power handed down to producing regency governments enables them to engage with the profit-maximization problem described in Section 2.1, these newfound revenue streams provide the incentive.

Table 1: Post-2001 oil and gas revenue splits (in percentages)

	Central government	**Province**	**Regency/city**	
			Producing	**Non-producing**[13]
Oil	84.5	3.1	6.1	6.1
Gas	69.5	6.1	12.2	12.2

[10] A second important policy change occurred in the ESDM regulation No. 30 2017, in which the gross-split PSCs were introduced. This radically restructured the contracts to focus on shares based on total revenue rather than profits. This switch should induce a homogenous change in extraction across all regencies and the time-specific effects in my panel data will account for it.

[11] Under PSCs, Independent Oil Companies (IOCs) assume the risk of exploration and development. If a commercially viable discovery occurs, the IOCs retain the production rights over the stipulated period. Once they begin to generate oil and gas revenues, the PSC involves a reimbursement scheme in which the share of the production revenues going to the government will instead cover some of the initial exploration and development costs. Hence, only once a discovery has occurred, does the government begin to internalize the costs.

[12] Article 21 §1: "The consultation with regional governments as meant in this provision is needed to ensure that the proposed plans for the development of fields can be coordinated with regional governments of provinces, especially for regional layout plans and plans for regional revenue from petroleum and natural gas in the regions in accordance with laws in force"

[13] While non-producing regencies also receive a share of the revenues, they do not partake in the decision-making process of whether to extract or not. I therefore restrict my sample to only the producing regencies.

3.2 Identifying prices

World oil prices are exogenous simply because Indonesian regencies are so small that they are price takers. Studies tend to attribute fluctuations in oil and gas prices to strategic behavior by OPEC countries (Chen et al. 2016; Kilian 2008), financial speculation (Roberts and Ryan 2015), and environmental regulations (Managi and Kumar 2008), global trends that Indonesian regencies, even collectively, are unlikely to influence. As a non-OPEC country, Indonesia cannot significantly impact world oil prices. The change in the independent variable across time is, thus, driven entirely by exogenous world price fluctuations.

I also consider natural gas prices. The correlations in Table 3 show that oil and gas prices move closely (2002-2018). Nonetheless, it is worth considering the case of gas prices motivating the extraction decisions. While it has traditionally been regarded as an additional benefit to oil extraction, the relative importance of natural gas has grown, with some even believing it might overtake oil as the prime fuel by 2030 (Economides and Wood 2009).

3.3 Identifying corruption

I operationalize corruption using a measure unlikely to fluctuate over my sample period, the Ethnic Fractionalization Index (EFI). The EFI indicates the probability that two randomly chosen individuals from the regency belong to different ethnic groups. In other words, the higher the EFI, the more fractionalized one should expect the area to be. The logic of this measure is that it captures a deeper cultural mechanism that induces patronage and social exclusion, namely systemic corruption. To disentangle the reverse causality concerns, I need it to remain constant over time; any temporal variation would make it unclear whether the measure's potentially endogenous qualities or the exogenous price variations explain the observed effect.

In this sense, the EFI is useful as it does not show much variation over the medium-term. Kaufmann (2015) provides a comprehensive study in which the cross-national variation of the EFI is largely exogenous to modern politico-economic shifts. Alesina et al. (2003) argue that at the national aggregate level, ethnic fractionalization indices are generally taken as exogenous in regressions over a 30-year timespan. Whether this also holds for my Indonesian study is less apparent. Arifin et al. (2015), however, suggest so. In a comparison between the 2000 and 2010 Indonesian population censuses, they find that internal migration remained low, due to improvements in transportation systems allowing for circular migration (such as seasonal work and long-distance commuting). According to Statistics Indonesia (BPS), internal migration decreased even more over the following decade (Nurhalima and Putri Ilhami Firdaus 2023). EFIs are, thus, likely even more stable in the latter part of my sample period. In Section 7, I also show that results are robust when using older ethnic composition data.

Whether EFI is useful for measuring corruption, however, requires more substantiation. The literature on ethnic composition suggests so (Alesina et al. 2003; Easterly and Levine 1997; Mauro 1995). Acemoglu et al. (2004) discuss how kleptocracy deepens if large oil rents can be used to bribe decisive groups exist. Beyond resource windfalls, Svensson (2008) shows how unconditional foreign aid windfalls can worsen corruption if the recipient country's ethnic composition is significantly fractionalized. Alesina et al. (2003) argue that ethnic fractionalized areas find it harder to reach political consensus and that ethnic groups are likelier to limit out-group access while capturing resources for themselves. They show in a global study that ethnic fractionalization correlates negatively with several measures of institutional quality, including corruption.

In a second round of estimations, I apply audit scores available at the regency level. The Indonesian Ministry of Finance assesses the accuracy and transparency of financial reporting by regency governments. To do so, they verify whether regency governments comply with national financial management regulations. These audits receive a score, which is suggested to correlate with the level of corruption in a regency. For instance, more corrupt regencies are likelier to engage in bookkeeping tricks that facilitate their corrupt behavior, and should, therefore, receive higher (worse) BPK audit scores on average.

Audit scores are useful to identify a different set of corruption characteristics not captured by the EFI. Such scores are publicly available information and audit boards tend to use their authority to signal budgetary transgressions to the public. Unlike the EFI, therefore, such scores point to a more visible form of corruption involving the embezzlement of public funds (Ferraz and Finan 2011). Comparing the results from these two indicators will shed light on what properties of corruption drive the observed effects.

While substantive, the literature across the social sciences remains highly contested on the appropriate measures (Malito 2014). While it would have been prudent to use the common corruption indices (e.g. Corruption Perception Index, Failed States Index, Sovereignty Index), I resort to using the EFI and audit scores because most are unavailable at the regency level. However, irrespective of the selected proxy, nearly all measures suffer from ontological and methodological issues and have been subject to serious reservations from the academic community (Langseth 2006).

3.4 Identifying drilling activity

I identify extraction behavior by measuring the drilling activity of each regency, that is, the number of wells each of them drill per year. While using the production-to-reserves ratio as my dependent variable seems like the most straightforward approach to measuring extraction rates, certain characteristics of the oil extraction process prevent it from being useful to this analysis. Oil extraction takes place in areas under high pressure. Once a well has been drilled, the pressure dictates the flow of hydrocarbons to the surface. As the well matures, the oil production rate will rapidly increase and plateau before pressure begins to weaken as the well approaches depletion causing the rate to decrease asymptotically (known as Darcy's Law). This pattern is exogenously determined and (Anderson et al. 2018) and Mason and Veld (2013) show that it renders oil production unresponsive to oil price fluctuations. Although this process is well understood in the engineering literature, economic studies have largely overlooked it.[14]

In addition to market price fluctuations, well drillings are likely influenced by the quantity of oil and gas reserves. Of particular concern here are discovery shocks, which will raise the available stock, extend the optimal extraction path $(T - t)$ from equation (3), and thus increase the extraction rate. Such shocks do not seem to be a concern. According to the Indonesian Petroleum Association, until early 2019, no significant discoveries had occurred since the 2001 discovery of Banyu Urip Field in East Java (Upperline 2019). The absence of discovery shocks, which can significantly distort extraction behavior, implies that an econometric analysis is potentially feasible within the given sample period.

Lastly, drillings serve many purposes, from exploration to production and maintenance. Theoretically, exploration and production involve two related, but distinct decision problems (Bohn and Deacon 2000). While drilling for discovery is more speculative and influenced by geological factors, drilling for production focuses on efficiently managing the extraction of known reserves. Initially, it is essential to determine whether to conduct exploration activities in a particular country. If exploration is undertaken and oil reserves are discovered, the next step is to decide the proportion of those discovered reserves to extract annually. This paper is concerned with the latter decision-making process. In the following section, I discuss how I isolate drilling activity for production purposes, and in Section 7 I test whether my results hold for the exploration problem as well.

[14] For a good, undemanding primer, see Fanchi and Christiansen (2016).

4 Data

Table (2) provides the summary statistics of my sample. Below I discuss the data collection of my dependent, independent, and control variables.

Table 2: Summary statistics

Variable	Unit	Obs.	Mean	Std. dev.	Min	Max	Source
Wells drilled	Count	476	5.32	16.39	0	126	ESDM
EFI	0-1	476	0.58	0.26	0.02	0.84	Arifin et al. (2015)
Audit score	0/1	369	0.13	0.33	0	1	INDO-DAPOER
Crude oil price (real)	$US per barrel	476	68.61	23.07	31.26	106.44	Littler (2017)
LNG price, Japan (real)	$US per MMBtu	476	9.87	2.87	5.38	15.06	Littler (2017)
Oil reserves	MMSTB	476	144.30	217.65	7.83e-07	1082.46	ESDM
Gas reserves	TSCF	476	0.68	0.77	4.69e-08	4.14	ESDM
Partition last year	0/1	476	0.02	0.13	0	1	Manually computed
Election last year	0/1	476	0.14	0.35	0	1	Balboni et al. (2021)
GDP per capita	Million IDR	476	45.57	63.17	0.55	375.41	INDO-DAPOER

Note: Statistics in this table refer to all oil-producing regencies between 2002 and 2018. Regencies created during the sample period are not included. The audit score dummy shows fewer observations because data is only available from 2005. 0/1 indicates a dummy variable. 0-1 indicates a continuous variable between 0 and 1.

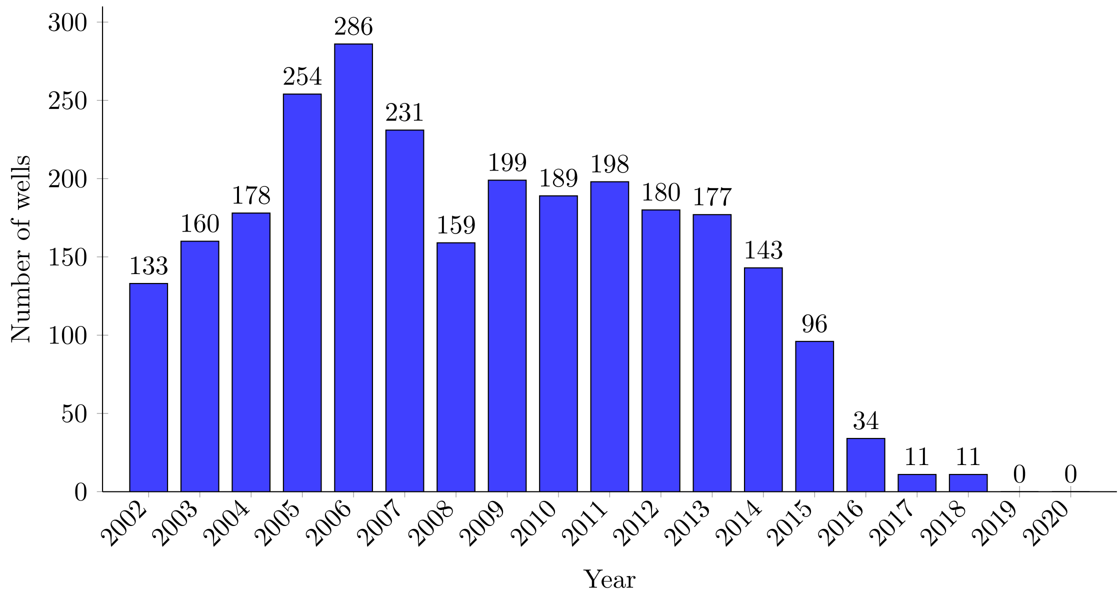
4.1 Dependent variable

The intended extraction rate is measured as the number of wells drilled, indicating the amount of oil a resource owner wishes to extract in any given period. Access to drilling information was made publicly available by the Ministry of Energy and Mineral Resources in 2020 (ESDM 2020) (see Appendix 10.5 for the full data scraping method). The data contains detailed information on every well drilled since the 1970s. This allows me to filter my observations to only development wells (those drilled for extraction purposes as opposed to exploration or restoration), those drilled within my sample period (2002-2018), and identify which regency they belong to.[15] The dependent variable is, thus, the number of wells drilled within a given regency and year.

Observing the mean, max value, and standard deviation from Table 2 makes it apparent that the distribution of this variable is non-normal. This is unsurprising as it is a combination of two different distributions in which one follows from a discrete decision ("To drill or not to drill?") while the subsequent decision is a continuous one ("How much to drill?"). Furthermore, the max value in my sample, which is from one regency in 2007, makes up nearly half of the total wells drilled that year. Indeed, only a small subset of regencies carry out most of the drilling activity. The final sample identifies 2639 wells drilled within the sample period. As Figure 2 illustrates, drilling activity has steadily decreased since its peak in 2006.

[15]For offshore wells, I applied a distance measure to the nearest regency border. For any well beyond 12 nautical miles from shore, the central government retains 100 percent of the revenues (Malden and Muhammadi 2019). I restricted the analysis to wells within the 12 nautical mile boundary.

Figure 2: Total number of development wells drilled per year



4.2 Independent variables

4.2.1 Ethnic Fractionalization Index (EFI)

The main independent variable is corruption, which I operationalize by applying the Ethnic Fractionalization Index. Mathematically, the following equation describes the calculation of the EFI:

$$EFI_j = 1 - \sum_{i=1}^{N} s_{ij}^2 \tag{10}$$

Where s_{ij} is the proportion of ethnic group i in region j. The index is a continuous variable ranging from 0 to 1 where 0 indicates that every person belongs to the same ethnic group and 1 if each person represents a different ethnic group. Due to the absence of year-to-year survey data on ethnicity, I resort to regency-level EFI calculations from the 2010 census for my analysis (*2010 Sensus Penduduk*).[16] The data for this variable comes from (Arifin et al. 2015) who use this census to calculate regency-level EFIs. Assuming ethnic composition remains constant over the 17 years (see Section 3.3), I apply this value to all year-observations within the sample period. Furthermore, Figure 2 indicates no particular abnormalities in the distribution of the EFI.

4.2.2 (Real) Oil and gas prices

Yearly world oil and gas prices are directly taken from the historical nominal oil prices in the World Bank Pink Sheet (Littler 2017). Because resource owners will make extraction decisions based on the real value of oil and gas, I adjust for inflation using Indonesian consumer price index data at constant 2010 $US, also from the World Bank. Units are in $US per barrel. For natural gas, it is suggested that natural gas prices are more regionally dependent (Economides and Wood 2009). It seems more precise, therefore, to use the Japanese liquefied natural gas (LNG) prices.[17] I again convert to real prices at the constant 2010 $US. Units are in $US per Million Metric British thermal units (MMBtu).

[16] In Indonesia, population censuses based on ethnicity were only carried out three times: In 1930 by the Dutch administration, and in 2000 and 2010 by BPS-Statistics Indonesia. Hence, in the 2020 census, it was again scrapped from the survey (Gunawan 2024).

[17] Japan is the largest LNG importer in the world and will likely be the price setter for East and Southeast Asia.

4.2.3 Audit scores

In my alternative regression, I use audit score as an optional measure of corruption. Audit data is from the World Bank (INDO-DAPOER) Indonesia Database for Policy and Economic Research (World Bank 2022). This data measures the financial compliance of regencies qualitatively using nominal values from 1-7. I consider unqualified and qualified opinions as compliant (audit scores 1, 2, and 5, respectively), while disclaimers and adverse opinions are considered non-compliant scores (3 and 4, respectively).[18] I converted these values into a dummy variable by assigning 0 to the compliers and 1 to the non-compliers (evidence of corruption). Notably, the mean across the sample lies at 0.13 (see Table 2). This implies that only about 3.6 regencies are non-compliant in a given year. This low amount of variation could limit the statistical potential of the data.

4.3 Control variables

The inclusion of both time and regency-specific effects into my panel data implies that included control variables need to vary both between regencies and across time. As such, my model already accounts for a wide range of variables. For instance, geographic variables (e.g., land area, sediment types, neighbors) will generally be colinear with the regency-specific effects in my model. Similarly, the time-specific effects will subsume most macroeconomic indicators (oil demand, technological change, nationwide policies).

4.3.1 Partitions

Since the decentralization of Indonesia, there has been a proliferation of new regencies, which should impact the variation in the dependent variable. In nearly all cases, these new regencies grew out of existing ones. I, therefore, generate a partition dummy for existing regencies that lost a part of their jurisdiction, where 0 are normal years and 1 indicates the first full year following a separation.[19] Because the SAR model requires a strictly balanced dataset, regencies created during the sample period were omitted. Following many of these splits, several corruption cases surfaced (Ramadhan 2012).[20] These regency partitions, thus, concern the analysis for two reasons: firstly, splits could have been motivated by resource capturing. If only a part of the regency is rich in oil and gas deposits, sub-district governments (*Kecamatan*) in these areas would have incentives to push for separation. In cases where they succeeded, this would likely affect their extraction behavior after the split. Secondly, the ethnic composition of the affected regencies is likely to jump exogenously. To combat this, I recalculate the EFI for regencies' pre-separation years, using a population-weighted average of the host and offshoot regencies' EFIs.

4.3.2 Oil and gas reserves

Additionally, behavior is likely dependent on the abundance of the resource (Kemal and Lange 2018). Without specific data on regency-level oil and gas reserve quantities, I employ spatial analysis tools to estimate the fraction of an oil field belonging to a given regency's jurisdiction. I multiply this fraction by the total stock of the oil field (that is, the sum of the proven (P1), probable (P2), and possible (P3) reserves), to which the regency belongs. This stock decreases yearly depending on the aggregate extraction rates in each field. Yearly data on each oil field's reserves are gathered from the General Directorate of Oil and Gas's Statistics Book (Directorate

[18] 6 indicates a newly proliferated state and no audit reporting is required. I encode these as null values. 7 indicates the audit report is in progress. These anomalies are succeeded by completed audit reports in the following years. In the two instances where this occurs, they are followed by consecutive negative audit report scores. I impute these as 1 (indicating financial corruption).

[19] I use the first full year after separation as I assume a lag effect on oil and gas drillings due to the duration between this change and new contracts being negotiated.

[20] Kutai Kartanegara regency government, for instance, faced a battery of corruption charges involving 34 officials following its split. It also holds the highest drilling activity (1171 wells drilled between 2002 and 2020) and one of the highest EFIs (0.80) in my dataset.

of Oil and Gas 2024).[21] The unit is in a million stock tank barrels (MMSTB) for oil and trillion standard cubic feet (TSCF) for gas.

4.3.3 Election year

Lastly, the literature has already suggested a link between the cyclicality of elections and resource extraction behavior among local governments (Balboni et al., 2021; Robinson et al., 2006). Similarly to partitions, I expect the effects of elections on drilling to have a lag effect and leverage the publicly available dataset from Balboni et al. (2021) to add an election dummy equaling 1 if an election occurred last year and 0 otherwise.

4.3.4 GDP per capita

Hamang (2024) discusses how more economically developed areas will attract more drilling companies. I, therefore, control for regencies' GDP per capita using GDP and population data from the World Bank INDO-DAPOER database (World Bank 2022). The unit is a million Indonesian Rupiahs (IDR). One concern here is the potentially high negative correlation between GDP per capita and the EFI: more ethnic fractionalization is more common in poorer areas (Alesina et al. 2003; La Porta et al. 1999). Because the independent variable is likely to affect the GDP per capita, including it in the regression may introduce a *bad control* in the estimation. Thus, whether to control it or not is debatable. I address this possibility in my robustness checks in Section 7.

5 Empirical method

Many within-country estimations suffer from some form of spatial spillover of the relevant variables. Mine is no different. While the potential for resource extraction behavior to spill over across borders remains relatively unexplored, previous empirical studies have already suggested the possibility of spillover effects in corruption (Donfouet et al. 2018; Khodapanah et al. 2022). Hence, my empirical method depends on the level of spatial autocorrelation of my independent and dependent variables.

I first concern myself with the spillover of ethnic groups. Realistically, one should expect a significant spatial correlation across regencies. Ethnic groups in Indonesia tend to cluster themselves within regions. In the case of Indonesia, this is likely even more apparent as the movement of peoples between neighboring regencies might be relatively easy compared to regencies further away, separated by bodies of water and dense rainforests. In Appendix 10.3, I test the potential for such a spillover, using Moran's I for spatial correlation, which returns significant results at the 1-percent level. As Figure 3 shows, if the ethnic fractionalization is above the global average (a positive z-score), the weighted average of its neighbors is likely to be so as well. Unsurprisingly, Figure 4 corroborates this by showing that neighboring regencies tend to have similar levels of EFI.

[21] No data per oil field is available before 2011. For this, I calculate values using available data on the total Indonesian reserve and multiplying it by the average share of each oil field's stock over the 7 years they are reported. This assumes the proportions of the oil reserves remain the same as in the available data. This might be considered a strong assumption.

Figure 3: Moran scatterplot of EFI

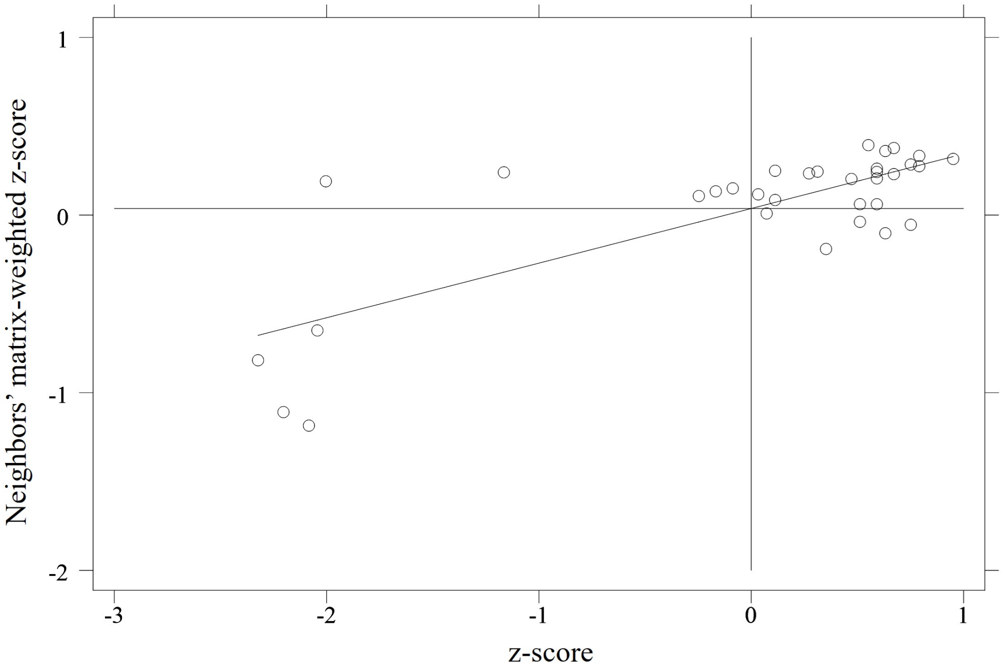
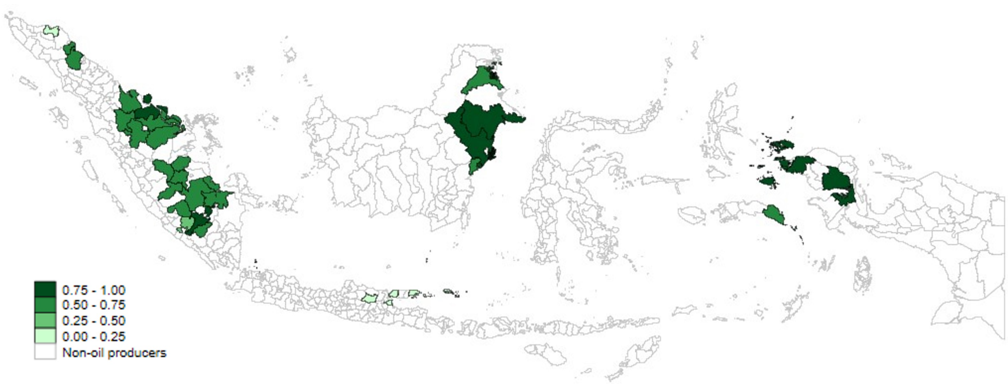


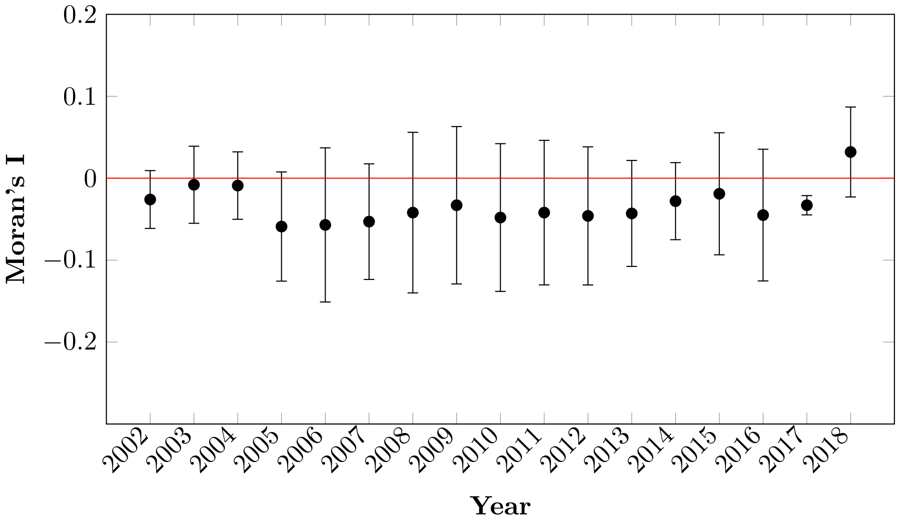
Figure 4: Spatial distribution of EFI



I also consider whether the drilling activity in one regency possesses similar spatial correlations. Running the same Moran's I test reveals only a weakly negative but non-significant spatial correlation (see Figure 5. This result appears to hold, even for local measures of spatial autocorrelations, observing regencies within the same oil field. Here, two opposing mechanisms could explain the result. The rivalrous nature of oil and gas resources affects the availability in other parts of the oil field. This zero-sum game might deter oil and gas companies from operating near one another. Conversely, local governments likely measure their economic performance more closely against neighboring regencies. This yardstick effect within oil-producing regencies might induce codependent policies that raise extraction rates. If one regency outcompetes the other by increasing its drilling activity, neighboring regencies might follow suit to "meet the benchmark"(Revelli and Tovmo 2007). These counteracting mechanisms may negate the spatial correlation, or extraction behavior might be entirely spatially independent.

The spillovers in the independent variable necessitate a spatial component in my regression. I, therefore, opt for a spatial autoregressive (SAR) model with two-way fixed effects (FE). Using random effects (RE) could potentially improve the model's efficiency. In Hausman tests, I find

Figure 5: Moran's I measure for global spatial autocorrelation
Number of development wells drilled



Note: The error bars represent the 95% confidence intervals.

that there is no significant difference between fixed effects and random effects model (see Appendix 10.4) when using the EFI as my corruption proxy, but significant differences when using audit scores. However, applying random effects might reintroduce endogeneity because it would use variation within and across regencies, leading to the corruption variable not completely dropping out. I report both models in my regression results when using the EFI, but not for the audit scores as the assumption of no systematic difference between the models is violated here. Nevertheless, because my interaction term depends on the invariance of the corruption variable to make causal claims, I rely primarily on the results using the less efficient, but more consistent fixed effects. Thus, the estimation model takes on the following structure:

$$D_{it} = \gamma_i + \lambda_t + (\theta W)\,\beta_1\,(EFI_i \times P_t) + \boldsymbol{\beta X}_{it} + u_{it} \tag{11}$$

$$u_{it} = (\psi W)u_{it} + \varepsilon_{it} \tag{12}$$

where D represents the number of oil and gas wells drilled, EFI is the ethnic fractionalization index, P is the world price of oil, and $\boldsymbol{X}$ is a vector of control variables that vary across time and regencies. Note that oil prices vary only across time and are subsumed by the time-specific effect, λ_t, while the EFI is time-invariant and subsumed by the regency-specific effects γ_i.[22] W represents the spatial weighting matrix, with parameters θ and ψ, respectively.[23] A significant and positive β_1 will mean that an increase in the price will cause more corrupt regencies to drill relatively more than the non-corrupt, supporting the discounting effect. Conversely, a negative coefficient would support the disinvestment effect.

The results are sensitive to the choice of weighting matrix. I opt for a distance-decay neighbor definition, which best reflects the First Law of Geography from Tobler (1970) that "everything is related to everything else, but near things are more related than distant things." Ideally, substantive theory should guide how I define neighbors. Unfortunately, substantive theory regarding spatial effects remains an underdeveloped research area (Darmofal 2015). It is imperative, thus, to reflect closely upon the properties of the sample. Indonesia is the largest archipelagic state in the world, with over 17,000 islands. Furthermore, the group of oil-producing regencies (28) is relatively small compared to the total (514), resulting in low amounts of spatial contiguity within

[22] As mentioned, audit scores, vary across time. I therefore need to add it as an additional control variable.

[23] I also concern myself with the potential spatial spillover of control variables, where Moran's I test for reserves and GDP per capita suggests strong correlations across regencies (see Appendix 10.3. I apply the model's weighting matrix accordingly.

the sample and a high number of disconnected observations (islands). A contiguity-based matrix might not account for the spillover effects within this sample. Despite the sensitivity of the results, the findings remain robust to the choice of the matrix (see Section 7).

I set the sample period with the identification considerations and data restrictions in mind.[24] Setting 2002 as my starting year allows me to account for two considerations: I expect a time lag for new PSC contracts following the implementation of the 2001 decentralization policy. Furthermore, a wave of new regencies emerged in 2001, of which some were relevant oil producers. Setting the starting point after this wave allows me to include them in my sample. Ending in 2018 avoids including year observations after the massive discovery shock for the South Sumatran regencies.[25]Furthermore, the ESDM changed significantly how they measured oil and gas reserves after 2018, limiting the usability of the data beyond then.

One drawback of the spatial autoregression is its need for a strictly balanced sample. It, therefore, precludes any new regency created after 2002 (see Appendix 10.2 for affected regencies). I also apply a strict definition of oil-producing regencies: any regency having drilled for production and received oil rents in any year within the sample period. These two conditions reduce my sample to 476 regency-year observations.

6 Results

6.1 Correlations

Table 3: Correlation of relevant variables

	Wells drilled	**EFI**	**Audit score**	**Oil price**	**Gas price**	**Gas reserves**	**Oil reserves**
EFI	0.161*** (0.000)	1.000					
Audit score	0.102** (0.029)	0.120*** (0.010)	1.000				
Oil price	0.101** (0.015)	0.008 (0.844)	0.205*** (0.000)	1.000			
Gas price	0.064 (0.124)	0.007 (0.868)	0.030 (0.528)	0.876*** (0.000)	1.000		
Oil reserves	0.161*** (0.000)	0.162*** (0.000)	-0.193*** (0.000)	-0.028 (0.501)	0.013 (0.760)	1.000	
Gas reserves	0.033 (0.431)	0.140*** (0.001)	0.068 (0.149)	0.050 (0.227)	0.028 (0.505)	0.388*** (0.000)	1.000
GDP per capita	0.063 (0.130)	0.315*** (0.000)	-0.128*** (0.006)	-0.0705* (0.091)	0.094** (0.024)	0.004 (0.933)	-0.139*** (0.001)

t-statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: this table uses all oil-producing regencies, including those omitted from the baseline regression. See full list of regencies in Appendix 9.2

Table 3 presents the correlations for the main variables. Importantly, the EFI and audit scores show a significant positive correlation, explaining about 12 percent of the variation of one another. This suggests that while they both show some overlap in corruption, they capture different properties. I have argued that ethnic fractionalization (EFI) connects to corruption man-

[24]for my alternative regression using audit scores, data is only available from 2005. This reduces the regency-year observations to 312

[25]This would affect the following oil-producing regencies in my sample: Sarolangun, Tebo, Ogan Komering Ulu, Muara Enim, Lahat, Musi Rawas, Musi Banyuasin.

ifested by demographic cleavages, while budgetary mismanagement (audit score) is tied to financial corruption more generally. Furthermore, oil and gas prices and the EFI show no notable correlations, providing some reassurance for their exogenous properties and my model's validity. The world oil and East Asian LNG prices seem highly correlated as well.

The relatively high correlation between the GDP per capita and the EFI raises concerns about including it in my model.[26] Contrary to expectations, the results show a positive correlation: the more ethnically fractionalized, the wealthier the regency. Interestingly, GDP (not shown) shows almost no correlation with the EFI. It is plausible, therefore, that the highly ethnically fractionalized regencies tend to be sparsely populated, causing the resource wealth, to impact the economy even more. It is also worth stressing that the GDP per capita says little about the distribution of this wealth: since corruption increases with ethnic fractionalization, the group in power is likely to grab disproportionately more of the rents. Either way, the curious findings here warrant a robustness check (see Section 7).

6.2 Findings

The results from my estimation address the empirical strength of the two opposing hypotheses: the discounting and the disinvestment effect. Table 4 describes the baseline regression results. I first consider column (1), which presents the main findings from this study. For oil, using a fixed-effects model, the interaction term between EFI and oil prices (the variable of interest) shows a highly significant and positive result. As for the magnitude, the results indicate that a unit change in the interaction term affects 0.154 wells. More intuitively, if one compares two regencies, where one has a 1 percentage point higher likelihood that two random individuals belong to different ethnic groups (more ethnically fractionalized), then that regency will drill 0.035 more wells following an exogenous oil price increase of one standard deviation (about $US 23.07 per barrel). While this may seem very small, it is worth stressing the extraction potential of a well: a single successful well will produce several thousand barrels of oil over its lifetime. A small fraction of a well can bring significant oil revenues over time. Because the finding implies that the corrupt behavior engendered by ethnic fractionalization will raise the extraction rate, it rejects the alternative disinvestment effect (*H1b*) in favor of the discounting effect (*H1b*).

Following Section 3.2, I deem it prudent to run the regression using regional liquefied natural gas prices to see if it affects my model. Column (3) considers the case in which gas prices motivate the extraction decisions. The results are also positive. Using the same logic as above, comparing one regency to another with a 1 percentage point higher EFI, a one standard deviation increase in gas prices (about $US 2.87 per MMBtu), will lead to the more ethnically fractionalized regency drilling 0.032 more wells. The magnitude is, thus, nearly identical to the oil model and again confirms the discounting effect. Overall, the discounting effect dominates for oil and gas, much like the extensive literature on forestry in Indonesia has shown. Despite being inherently different resources, over-extraction of resources seems to be a general outcome of corruption.

In all but column (4), the spatial autoregression seems appropriate to my empirical study as the Wald test of spatial terms gives significant results. Interestingly, the error term is spatially correlated for oil, but not gas. This means that only when using oil indicators does the model provide a better fit for some areas than others. Lastly, the more efficient random effects model in columns (3) and (4) provides some reassurance for the results as the main effects are nearly identical for the respective interaction terms. However, they return widely different results for the spatial spillover effects of the EFI. Because the fixed effects only consider within-regency variation for which the EFI does not vary, the random effects will likely provide more reliable results since they incorporate between-regency variation. Therefore, the possible spillover effects of the EFI, remain unclear.

In Table 5 I entertain my second corruption measure, audit scores. Using the same specification,

[26] See Alesina et al. (2003) and La Porta et al. (1999) for a closer discussion on the relationship between GDP and Ethnic Fractionalization.

Table 4: The moderation effects of corruption on extraction: ethnic fractionalization as a proxy

	Dependent variable is the number of wells drilled			
	Fixed effects model		Random effects model	
	(1)	(2)	(3)	(4)
		Main effects		
EFI × Oil price	0.154***		0.150***	
	(6.53)		(6.33)	
EFI × Gas price		1.132***		1.127***
		(4.95)		(4.92)
Oil reserves	0.0281*		0.0222**	
	(1.90)		(1.97)	
Gas reserves		5.284		3.738
		(1.48)		(1.43)
GDP per capita	-0.0332**	-0.0375***	-0.0290**	-0.0328**
	(-2.26)	(-2.58)	(-2.04)	(-2.30)
Partition last year	-2.341	-2.927	-2.625	-2.997
	(-0.71)	(-0.87)	(-0.79)	(-0.89)
Election last year	0.450	0.0659	0.478	0.0739
	(0.37)	(0.05)	(0.39)	(0.06)
EFI			3.710	2.693
			(0.35)	(0.25)
Constant			-0.0181	0.179
			(-0.00)	(0.03)
		Spatial autoregressive coefficient		
EFI	553.7**	438.2	2.684	4.561
	(1.96)	(1.48)	(0.20)	(0.30)
Oil reserves	-0.0417		-0.0377	
	(-1.55)		(-1.61)	
GDP per capita	-0.0178	-0.0304	-0.0196	-0.0339
	(-0.63)	(-1.12)	(-0.72)	(-1.26)
Gas reserves		-7.682		-7.283
		(-1.33)		(-1.43)
Error term	-0.381**	-0.234	-0.348**	-0.220
	(-2.39)	(-1.58)	(-2.21)	(-1.48)
Wald test (χ^2)	13.07**	8.03*	10.12**	6.90
Observations			476	
Regencies			28	
Years			17	

t-statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table presents the spatial estimates for the oil and gas-producing regencies between 2002 and 2018. All models include a spatial lag of the EFI, GDP per capita, oil (or gas) reserves, and the error term. Columns (1) and (3) study the effect using oil indicators, while columns (2) and (4) apply gas indicators. For the random effects model, I include the direct effect of the EFI to account for the across-regency variation. Note that the added variation introduced by this model results in less reliable estimates for the interaction terms.

Table 5: The moderation effects of corruption on extraction: audit scores as a proxy

	Dependent variable is the number of wells drilled	
	Fixed effects model	
	(1)	(2)
	Main effects	
Audit score × Oil price	-0.0665	
	(-0.61)	
Audit score × Gas price		0.147
		(0.19)
Oil reserves	0.0432**	
	(2.03)	
Gas reserves		4.639
		(1.14)
GDP per capita	-0.0246	-0.0266
	(-1.20)	(-1.26)
Partition last year	0.646	-1.646
	(0.14)	(-0.35)
Election last year	1.060	0.961
	(0.72)	(0.63)
Audit score	7.414	-0.917
	(0.77)	(-0.10)
Constant		
	Spatial autoregressive coefficient	
Audit score	12.86***	13.29**
	(2.64)	(2.44)
Oil reserves	0.0302	
	(1.02)	
GDP per capita	0.0486	0.0287
	(1.62)	(0.92)
Gas reserves		11.29*
		(1.88)
Error term	-0.463***	0.283*
	(-2.88)	(-1.86)
Wald test (χ^2)	16.08***	12.35**
Observations	316	
Regencies	24	
Years	13	

t-statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: The table presents the spatial estimates for the oil and gas-producing regencies between 2005 and 2018. All models include a spatial lag of the audit score, GDP per capita, oil (or gas) reserves, and the error term. Column (1) studies the effect using oil indicators, while column (2) uses gas indicators.

I replaced the EFI with audit scores and found no evidence of an effect, neither for oil or gas. The statistically insignificant coefficients indicate that we cannot determine with any reasonable level of statistical confidence whether the effect deviates from 0. Accordingly, the results do not lend themselves to an evaluation of the hypotheses. It is entirely possible, relying on these results, that the discounting effect is larger, smaller, or equal to the disinvestment effect. In other words, while corrupt behavior engendered by ethnic rivalry (such as patronage) seems to affect extraction, corrupt behavior engendered by audit scores (such as the diversion of funds) does not show similar effects. It is worth noting, however, that the data is possibly underpowered: only 48 out of 316 regency-year observations indicate corruption (an audit score of 1) across my sample. While I argue that the discrepancy in the finding is likely caused by the different properties of corruption they capture, it is also possible that an effect might exist, but is undetectable using the current dataset.

Notwithstanding, the Wald tests reveal high χ^2-scores, so the SAR model is still relevant. Interestingly, the spatial autoregressive coefficients for the audit scores are significant. Unlike the EFI, the audit scores show slight within-regency variation, as some regencies jump from mismanaged to well-managed budgets and vice-versa. This means that the results from the fixed-effects models might be more reliable. These findings suggest that while audit scores show no evidence of an effect on extraction rates within regencies, they still correlate spatially with extraction rates. The discrepancy between the insignificant interaction term and the significant spillover effects may lend to considerable reverse causality. While the interaction term only depicts a causal relationship, the spillover effect from the audit scores could raise extraction rates as much as extraction rates, and the additional resource windfalls that follow could raise the audit scores. Finally, the error terms are significant, so the model's fit will vary depending on the regency.

7 Robustness checks

Many other components of this specification warrant further testing. I now restrict myself to the oil model from column 1 in the baseline regressions. Firstly, I re-run the specification with a contiguous spatial-weighting function. The choice between which weighting matrix to apply should be rooted in sound theoretical evidence of the spatial effect for the relevant variable. In the case of ethnic fractionalization, it will depend as much on the properties of the EFI as the local level characteristics with which it interacts (e.g. geography, political structure, culture, history, etc.). Because such granular research does not exist, I test my hypotheses using both matrices for completeness. I find comfort that the magnitude changes little (0.165) when switching between an inverse distance and a contiguity-based matrix.

Secondly, an important assumption for using EFI has been its temporal invariance. For regencies that existed before 2000, I can use the ethnic surveys from the population census of that year instead. As Ananta et al. (2013) highlight, however, the surveys are structurally quite different and any quantitative comparison of the two censuses should be cautioned. On the one hand, procedural issues of the 2000 survey led to a serious underestimation of some results, while on the other, a re-classification of several ethnic groups led to the 2010 survey providing a much richer dataset than previously possible. Nonetheless, I run the baseline regression from column (1) leveraging available data from Tajima et al. (2018) on the 2000 census EFIs. Using the less reliable 2000 census results in a near identical magnitude (0.160). While this is by no means indicative of the temporal invariance per se, it does suggest that under different survey specifications, the results remain unchanged.

Going further, when measuring corruption as a proportion of politicians with corruption-related convictions Dincer (2008) shows how it exhibits an inverse U-shaped relationship with the EFI. As convictions increase, the proportional increase in the EFI lessens. On the other hand, he finds that the Ethnic Polarization Index (EPI), which increases the more equal the largest ethnic groups become, remains linearly correlated with his corruption measure[27]. As with any corruption measure, the number of convictions also has limitations. For instance, it might not capture more corruption, but simply a higher willingness to address it. Nevertheless, it is relevant to consider this possibility in my estimations as well. The dataset fromArifin et al. (2015) also includes the EPI. I, therefore, substitute the EFI with the EPI and re-run the regression. The magnitude (0.140) drops ever so slightly. The summary statistics in Table 2) illustrates the wide range of EFI scores in my sample, going from 0.02 to 0.84. Despite these upper values potentially explaining less of the variation in corruption, my results do not seem too affected by this possible inverse U-shaped relationship.

Cust and Harding (2020) use a regression discontinuity across country borders and find that those with higher institutional quality (not necessarily corruption) engage in more search and discovery drilling. In other words, the disinvestment effect might potentially dominate in the search and discovery phase of the exploitation process.[28] However, the two phases consist of different maximization problems: drilling for discovery is more speculative and influenced by geological factors while drilling for production focuses on the efficient management and extraction of known reserves (Bohn and Deacon 2000). Nonetheless, I deem it empirically relevant to see whether my findings hold when using exploration wells instead. Using the same method to extract drilling data (see Appendix 10.5, I now filter for wells drilled for exploration purposes. Indeed, using exploration wells as the dependent variable, I find the magnitude drops to 0.013, thus by a factor of about 10. A price increase will still increase drilling activity in more corrupt regencies, but significantly less so. This finding does suggest that the combined discounting and disinvestment effect is substantially lower for the exploration problem than for production.[29] This makes sense. The discounting effect is potentially weaker in this part of the exploitation process as operating firms are unlikely to fear expropriation before any valuable deposit has been discovered. Still, regency governments might wish to extend more concessions due to short-sightedness. On the other hand, it is plausible that the disinvestment effect is stronger as it is usually in this phase where high upfront capital investments are needed. In any case, the sensitivity of my findings between exploration and production underlines the fundamental difference in the decisions that go into the two activities.

Lastly, following the concerns from the literature (Alesina et al. 2003; La Porta et al. 1999) and the curious results from the correlation table, dropping the potentially endogenous GDP per capita variable from the regression might affect the results. The direct effect remains relatively unchanged (0.139) when excluding it from the panel regression and the spatial weighting matrix. This provides some reassurance that the endogeneity concern might not be an issue for my estimation. Possibly, the inter-regency reallocation scheme (see Table 1 spreads revenues across neighboring regencies and limits the extent to which GDP per capita can affect the model.

8 Discussion

My study has shown considerable support for the discounting effect, that higher corruption leads to drilling for oil and gas above optimal. This finding is also robust to various considerations, thus going against some strands of the literature predicting under-extraction. This implies that resource owners will be more impacted by short-sightedness in their decision-making rather than

[27]Mathematically, the EPI is slightly different from the EFI: $EPI_j = 1 - \sum_{i=1}^{N} \left(\frac{0.5-s_{ij}}{0.5}\right)^2 s_{ij}$. As before, s_{ij} is the proportion of ethnic group i in region j. Unlike the EFI, the EPI reaches a maximum when there are two ethnic groups of equal size in a region

[28]This makes sense, it is often in this phase where higher upfront capital investments manifest. Combined with the increased uncertainty when carrying out discovery drilling, it is likely that the decision of whether or not to drill at all (which is when the disinvestment effect would occur) takes precedence for the resource owner in this phase of the oil exploitation process.

[29]It is also worth noting that running the regression with exploration wells using audit scores instead of the EFI, yields a significant and positive coefficient (0.036). While an increase in oil prices might show any evidence of an effect on the number of development wells drilled, it does seem to cause regencies with poorly managed budgets to drill more exploration wells. However, whether the source of this discrepancy is the conceptual differences between the two optimization problems or the lack of variation in the audit score data is unclear.

the potential disincentives to invest in the necessary resource capital brought by corrupt environments. In sum, it will raise resource revenues in the short run to the detriment of long-term social welfare and possibly the environment.[30]

With this in mind, how can governments properly address these detrimental effects of corruption? Only some types of corruption seem to drive this effect. Audit scores, for instance, do not show any evidence of such. Therefore, although supporting the work of the Audit Board of Indonesia (BPK) remains an important anti-corruption measure, it will likely not be sufficient to address over-extraction. On the other hand, how ethnically fractionalized a region is, seems to impact the extraction rates significantly. In this respect, corrective measures focusing on structural issues in governance, such as promoting equal representation, lowering ethnic tensions, and preventing in-group patronage might prove more effective.

Although audit scores show no direct effect on drilling, my findings show that they correlate spatially: oil-producing regions will likely also feel the impact of the discounting effect if other nearby regencies are financially corrupt. Thus, the spillover effects from neighboring areas might undermine efforts to mitigate corruption in a specific place. As such, it might be advantageous to address the issue more ambitiously by implementing policy responses with a regional or national scope.

Despite the clear takeaways from my analysis, it is not without its limitations. My research question seeks to answer how *changes* in corruption affect extraction rates. However, I can only observe its *variation*, because my corruption measure is constant across time. This is a small, but crucial distinction. For instance, if the disinvestment effect would dominate the coefficient of the interaction term would be negative. While increasing prices will always make extractions more attractive, in this case, the extraction increase would be less pronounced for more corrupt regencies. In other words, this finding would have supported my alternative hypothesis of under-extraction despite the total effect on drilling being positive. Thus, this interaction term cannot perfectly test the plausibility of the disinvestment effect. While the shift-share analysis allows me to disentangle the reverse causality concern of the corruption measure and show support for the over-extraction hypothesis, it is necessary to highlight the limitations in addressing this aspect of the research question.

The chosen measures for corruption used in this study are also not without limitations. Corruption can be defined as any *dishonest or illegal behavior, especially by powerful people*. Therefore, the Ethnic Fractionalization Index and the audit scores can only serve as explanatory variables for some corrupt behaviors, but certainly not all. My research question concerns the total effect of corruption on extraction, which this analysis cannot perfectly capture. It is conceivable that some behaviors, such as the ones identified in this study, induce over-extraction while the net effect is negative. In addition, the ambiguous results from using audit scores do not help to illuminate the possible heterogeneity across corrupt behavior.

The analysis is also limited by the narrow confines of the empirical setting: Indonesian oil-producing regencies between 2002 and 2018. The question then becomes: to what extent can this finding be extrapolated to other cases? For once, the findings might be dependent on the oil governance system. Indonesia pioneered production-sharing contracts (PSCs), which provided almost complete discretion in how and when IOCs could conduct their activities. Although many countries have since adopted similar PSC schemes, many other systems exist, providing varying degrees of regulatory oversight, power to state-owned enterprises, and revenue splits. Extensive research on the merits of different oil governance systems (Abdo 2014; Aguiar and Freire 2017; Thurber et al. 2011) suggest that the distortive effects of corruption could be subject to heterogeneity across countries. Additionally, the behavior of the resource owner might depend on considerations such as the infrastructure in place, the abundance of the resource, and expertise in the workforce. For

[30] The environmental impacts are not limited to the disruption of ecosystems, water contamination and deforestation. Karp (2017), for instance, describe how shifting more of the environmental damages caused by resource exploitation to the present can bring ecosystems towards a tipping-point in which it irreversibly changes to a new state with severe ripple-effects. Such tipping-points could be avoided by "spreading out" these damages over time.

instance, if a country has less available oil and gas infrastructure to transport the resources, the need for potential firms to supply more upfront capital investments might strengthen the disinvestment effect. The combined impact of all these parameters could change the magnitude or direction of my results.

In light of these limitations, several paths for future research exist. Firstly, it should consider alternative econometric techniques to disentangle the reverse causality concern of corruption and extraction. From the standard OLS method in Bohn and Deacon (2000), to the differences-in-differences in Kemal and Lange (2018) and regression discontinuity in Cust and Harding (2020), previous studies have used different approaches to improve the causal inferences. The shift-share analysis in this study is an extension of those efforts. It is useful to isolate the causal linkages properly, but keeping corruption constant over time limits its ability to assess this study's twin hypotheses perfectly. Future research should look for new empirical models and settings that will more closely approximate the theoretical predictions in the resource economics literature.

Secondly, extending research to different cases might reveal how externally valid the findings in this study are. Additional within-country estimations exploring how countries with different regulatory environments behave would help assess how persistent the discounting effect is. Importantly, it could potentially help provide policy insights into which oil governance systems can better mitigate the deleterious effects of corruption. Additionally, it would be helpful to understand to what extent oil and gas can be extrapolated to other resources. Despite the theoretical differences, my findings of a discounting effect for oil and natural gas are similar to what the literature has already shown for forestry in Indonesia. Many other resources, from renewables such as fisheries to non-renewables such as minerals, might be subject to similar effects. Only future research can establish how far these findings can be extrapolated.

Lastly, as the study makes no difference between the two agents involved in the drilling decision, some of the dynamics in this problem remain uncovered. A regency may increase its drilling through a firm intensifying its activity within its concession or the local government provisioning more permits. Theoretically, the former only concerns *perceived* corruption, while the latter is caused by *actual* corruption. On an aggregate level both outcomes result in more drilling, but understanding how much the respective agents contribute to the discounting effect will help sharpen the policy responses. For example, if the discounting effect is largely driven by firms increasing the drilling, policy responses could focus on trust-building campaigns rather than anti-corruption measures. Such firm-level well data is available but goes beyond the scope of this study. Therefore, future research is encouraged to leverage this data to uncover what mechanisms drive the discounting effect.

9 Conclusion

Could a deterioration in corruption cause the over-extraction of non-renewable resources? And if so, through what mechanisms? These questions are highly relevant considering how, according to a large body of literature, regions endowed with natural resources face greater susceptibility to corruption. If this corruption causes non-renewable resources to be over-exploited, it will limit long-term economic development and put more pressure on the environmental capacity of the region.

To discern, then, if over-extraction is the outcome, I investigated a sample of regencies in Indonesia endowed with oil and natural gas deposits. Here, I find considerable support for over-extraction. An exogenous increase in either oil or gas prices raises drilling activity (and consequentially extraction rates) disproportionately more in more corrupt regencies. This suggests that as the value of oil or gas rises, myopic incumbents with limited-term lengths and firms fearful that these rent-seeking incumbents will expropriate their concession in the future will seek to maximize the resource revenue streams over a shorter time frame, leading to over-extraction. This goes against some cross-country studies which suggest that a corrupt environment will reduce incentives to invest large, but often necessary capital to initiate a drilling project and reduce extraction rates. Instead, my study provides new evidence that corruption leads to less sustainable resource management and that this effect may spill over to nearby areas.

Furthermore, not all forms of corruption seem to engender this effect. Different corruption measures yield different results. Corruption rooted in the ethnic cleavages within a region (such as in-group nepotism, patronage, and social exclusion) reveals causal effects, while more overt corrupt behavior relating to financial malfeasance does not. The monetary gains an individual can acquire from an increase in the resource's value might be secondary to the potential for those gains to consolidate power for the greater ethnic group.

10 Appendix

10.1 Deriving the Optimal Extraction Rate

To derive the optimal extraction under uncertainty I first need to maximize the problem defined by equations (4) and (5). For simplicity, I convert it into continuous time:

$$\max\left\{R_t\right\}\int_{t=0}^{T}\Pi\left(R_t\right)e^{-(\mu+\rho)t}dt \tag{13}$$

$$s.t. \quad \dot{S}_t = -R_t \tag{14}$$

With marginal profits equaling net price, I can solve the Hamiltonian problem, with R as the choice variable and S as the state variable:

$$\mathcal{H}\left(R_t,\ S_t,\ \mu_t\right) = p_t R_t + \mu_t\left(-R_t\right) \tag{15}$$

With first-order conditions:

$$\frac{\partial\mathcal{H}}{\partial R_t} = p_t - \mu_t = 0 \iff p_t = \mu_t \tag{16}$$

$$\frac{\partial\mathcal{H}}{\partial S_t} = 0 \tag{17}$$

$$\frac{\partial\mathcal{H}}{\partial t} = \dot{\mu_t} = \mu_t(\mu+\rho) \tag{18}$$

$$\frac{\dot{\mu_t}}{\mu_t} = \frac{\dot{p_t}}{p_t} = \mu+\rho \tag{19}$$

Here, the final term is the modified Hotelling rule with expropriation risk. Assuming the initial price, p_0, is known, I can rewrite it as follows:

$$p_t = p_0 e^{(\mu+\rho)t} \tag{20}$$

This is the Hotelling efficiency condition. To find the optimal resource extraction, I also need to know the shape of the resource demand function. In this derivation, I assume an inverse demand function, whose price sensitivity (how much it responds to oil supplied, R) is given by a and choke price (the final price before the time at depletion) by p_T. Setting these two equations equal gives me the resource owner's optimal extraction:

$$p_T e^{-aR_t} = p_0 e^{(\mu+\rho)t} \tag{21}$$

$$p_0 e^{(\mu+\rho)T} e^{-aR_t} = p_0 e^{(\mu+\rho)t} \tag{22}$$

$$e^{(\mu+\rho)T-aR_t} = e^{(\mu+\rho)t} \tag{23}$$

$$(\mu+\rho)T - aR_t = (\mu+\rho)t \tag{24}$$

$$R_t = \frac{(\mu+\rho)\left(T-t\right)}{a} \tag{25}$$

10.2 List of regencies

Table 6: List of oil-producing regencies

Regency	Province	Largest group	EFI	Total wells	Oil rent (avg. IDR)
Aceh Utara	Aceh	Acehnese	0.10	7	4 638 712
Balikpapan (city)	East Kalimantan	Javanese	0.76	47	2 713 103
Bangkalan	East Java	Madurese	0.05	9	2 624
Batang Hari	Jambi	Malay	0.56	5	29 254
Bengkalis	Riau	Javanese	0.77	113	9 709 375
Bojonegoro	East Java	Javanese	0.02	1	53 024
Bontang (city)	East Kalimantan	Javanese	0.77	59	13 100 000
Bulungan	North Kalimantan	Dayak	0.75	1	56 654
Kampar	Riau	Malay	0.68	103	1 908 500
Thousand Islands	Jakarta	Betawi	0.76	30	495 269
Kutai Kartanegara	East Kalimantan	Javanese	0.80	1167	11 000 000
Kutai Timur	East Kalimantan	Javanese	0.84	5	131 851
Lahat	South Sumatra	Malay	0.31	1	131 373
Langkat	North Sumatra	Javanese	0.62	2	280 582
Muara Enim	South Sumatra	Malay	0.79	2	1 336 941
Musi Banyuasin	South Sumatra	Musi	0.61	189	3 274 959
Musi Rawas	South Sumatra	Javanese	0.73	1	535 290
Ogan Komering Ulu	South Sumatra	Ogan	0.63	58	283 814
Pelalawan	Riau	Malay	0.75	2	60 463
Rokan Hilir	Riau	Javanese	0.67	98	3 885 838
Rokan Hulu	Riau	Javanese	0.72	4	80 768
Sarolangun	Jambi	Malay	0.54	20	37 974
Siak	Riau	Javanese	0.75	504	6 165 360
Sidoarjo	East Java	Javanese	0.08	1	162 862
Sorong	West Papua	Javanese	0.80	44	544 127
Sumenep	East Java	Madurese	0.09	15	161 503
Tanjung Jabung Barat	Jambi	Javanese	0.75	1	51 926
Tebo	Jambi	Malay	0.58	42	7 176
	Excluded oil-producing regencies				
Aceh Tamiang	Aceh	Javanese	0.69	1	169 922
Banyuasin	South Sumatra	Javanese	0.73	1	318 659
Meranti Islands	Riau	Malay	0.64	14	-338 878
Penajam Paser Utara	East Kalimantan	Javanese	0.74	37	323 266
Raja Ampat	West Papua	N/A	0.79	1	118 565
Seram Bagian Timur	Maluku	Seram	0.63	33	4 912
Teluk Bintuni	West Papua	N/A	0.91	1	-1 175 048

Note: The excluded oil-producing regencies were created after the starting year of the sample period (2002). Because the SAR model requires a strictly balanced sample, they were not used in the regression.

10.3 Moran's I test

Table 7: Test for Global Spatial Autocorrelation

	Drilled wells	EFI	Audit score	GDP per capita	Oil reserves	Gas reserves
2002	-0.026	0.322***	-	0.09***	0.283***	0.122***
	(0.61)	(5.995)	-	(3.524)	(5.717)	(2.983)
2003	0.009**	0.307***	-	0.079***	0.286***	0.144***
	(1.735)	(5.489)	-	(2.989)	(5.546)	(3.229)
2004	-0.009	0.309***	-	0.097***	0.299***	0.012
	(0.991)	(5.604)	-	(3.475)	(5.836)	(0.786)
2005	-0.059	0.309***	-	0.12***	0.3***	0.017
	(-0.861)	(5.604)	-	(3.994)	(5.854)	(0.881)
2006	-0.057	0.309***	0.439***	0.137***	0.303***	0.004
	(-0.566)	(5.604)	(7.115)	(4.043)	(5.899)	(0.652)
2007	-0.053	0.309***	0.495***	0.146***	0.3***	0.014
	(-0.619)	(5.604)	(7.93)	(4.062)	(5.847)	(0.822)
2008	-0.042	0.306***	0.215***	0.151***	0.3***	0.014
	(-0.23)	(5.536)	(3.751)	(4.127)	(5.847)	(0.822)
2009	-0.033	0.305***	0.125***	0.162**	0.3***	0.018
	(-0.06)	(5.534)	(2.355)	(4.218)	(5.844)	(0.896)
2010	-0.048	0.302***	0.171***	0.137***	0.315***	0.012
	(-0.393)	(5.687)	(3.212)	(3.003)	(6.275)	(0.818)
2011	-0.042	0.302***	0.181***	0.137***	0.316***	0.006
	(-0.277)	(5.687)	(3.474)	(2.975)	(6.296)	(0.695)
2012	-0.046	0.302***	-0.018**	0.14***	0.327***	0.041
	(-0.394)	(5.687)	(1.992)	(3.015)	(6.537)	(1.228)
2013	-0.043	0.302***	-0.018**	0.134***	0.32***	0.041*
	(0.344)	(5.687)	(1.992)	(2.933)	(6.365)	(1.308)
2014	-0.028	0.302***	-0.018**	0.130***	0.319***	0.023
	(0.024)	(5.687)	(1.992)	(2.878)	(6.35)	(0.996)
2015	-0.019	0.302***	-0.035	0.122***	0.316***	-0.002
	(0.263)	(5.687)	(-0.806)	(2.759)	(6.275)	(0.283)
2016	-0.045	0.302***	-0.035	0.113***	0.3***	0.005
	(-0.376)	(5.687)	(-0.806)	(2.618)	(5.922)	(0.692)
2017	-0.033	0.302***	-	0.111***	0.298***	0.007
	(-0.526)	(5.687)	-	(2.592)	(5.925)	(0.73)
2018	0.032**	0.302***	-	0.102***	0.296***	-0.012
	(2.183)	(5.687)	-	(2.464)	(5.88)	(0.393)

z-statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ (all tests are one-tailed)

Note: Audit scores have no observations between 2002 and 2004. 2005, 2017, and 2018 have too little spatial variation.

10.4 Hausman test

	χ^2-statistic	p-value
Regression 1 (EFI × oil price)	3.79	0.580
Regression 1 (EFI × gas price)	5.32	0.379
Regression 3 (Audit score × oil price)	16.79***	0.010
Regression 4 (Audit score × gas price)	18.02***	0.006

Note: Test of H_0: Difference in coefficients ($\beta_{fe} - \beta_{re}$) is not systematic.

10.5 Data scraping instructions for well drilling

10.5.1 Step 1: Extracting the data

First, you need to acquire a .HAR file from ESDM One Map (only in Indonesian). This is done by clicking "Daftar Peta" in the top right corner, finding the "well" layer from the subsequent drop-down menu, and selecting "ADD". Then click "Peta Aktif", select the three-dotted symbol to the right of the "wells" layer, and open its attribute table (the bottom option). The data is large, containing around 31,000 wells since 1975. It is, therefore, recommended to narrow down to dataset to those drilled after 2001 before scraping. With the attribute table for the "wells" layer open, select F12 on your keyboard to inspect the website. Go to the "network" tab in the newly opened window. Keep it open, while turning the attention back to the attribute table. Start scrolling down the table and files will start to appear in the "network" tab as you go. Once at the bottom of the attribute table is reached, type "JSON" in the filter bar within the "network" tab so only the relevant files appear. Right-click on any of them and choose "save all as HAR". The saved file will have a name along the lines of "geoportal.esdm.go.id_Archive.har[date]".

10.5.2 Step 2: Parsing the raw data

I use Excel's Power Query in this step. Upload it to Excel by selecting "Data" → "Get data" → "From file" → "From JSON". Once the right file is selected, click "Load data" and the Power Query Editor will open. Now copy-paste the following functions in the formula bar, one after the other, to extract the table data:

```
= Json.Document(File.Contents("C:\Users\...\geoportal.esdm.go.id_Archive.har"))
= log[entries]
= Table.FromList(entries, Splitter.SplitByNothing(), null, null, ExtraValues.Error)
= Table.ExpandRecordColumn(#"Converted to Table", "Column1", {"response"}, {"response"})
= Table.ExpandRecordColumn(#"Expanded Column1", "response", {"content"}, {"content"})
= Table.ExpandRecordColumn(#"Expanded Column1.response", "content", {"text"}, {"text"})
= Table.TransformColumns(#"Expanded Column1.response.content",{},Json.Document)
= Table.ExpandRecordColumn(#"Parsed JSON", "text", {"features"}, {"features"})
= Table.ExpandListColumn(#"Expanded text", "features")
= Table.ExpandRecordColumn(#"Expanded features", "features", {"attributes"}, {"attributes"})
= Table.AddColumn(#"Renamed Columns", "C_x", each if [x] = null then [LAT] else [x])
= Table.AddColumn(#"Renamed Columns", "C_y", each if [y] = null then [LONG] else [y])
= Table.RemoveColumns(#"Added Conditional Column",{"LAT", "LONG","x","y"})
```

Load and save the data.

10.5.3 Step 3: Creating offshore borders for regencies

In ArcGIS Pro, I create the 12 nautical mile offshore boundaries for regencies, as described by Malden and Muhammadi (2019). This way wells will be assigned to their proper regencies. I use Thiessen polygons to create realistic offshore border divisions.

```
arcpy.analysis.Buffer(
    in_features="IDN_Country",
    out_feature_class=r"C:\Users\...\Default.gdb\IDN_Country_Buffer",
    buffer_distance_or_field="12 NauticalMilesInt",
    line_side="OUTSIDE_ONLY",
    line_end_type="ROUND",
    dissolve_option="ALL",
    dissolve_field=None,
    method="PLANAR"
)
arcpy.management.SelectLayerByLocation(
    in_layer= "IDN_Kabupaten",
    overlap_type= "INTERSECT",
    select_features= "IDN_Country_Buffer",
```

```
    search_distance=None,
    selection_type="NEW_SELECTION",
    invert_spatial_relationship="NOT_INVERT"
)
arcpy.management.FeatureVerticesToPoints(
    in_features="IDN_Kabupaten",
    out_feature_class=r"C:\Users\...\IDN_Kabupaten_FeatureVertice",
    point_location="ALL"
)
arcpy.analysis.CreateThiessenPolygons(
    in_features="IDN_Kabupaten_FeatureVertice",
    out_feature_class=r"C:\Users\...\IDN_Kabupaten__Thiessen",
    fields_to_copy="ALL"
)
arcpy.analysis.Clip(
    in_features="IDN_Kabupaten_Thiessen",
    clip_features="IDN_Country_Buffer",
    out_feature_class=r"C:\Users\...\Thiessen_Clipped",
    cluster_tolerance=None
)
arcpy.management.Dissolve(
    in_features="Thiessen_Clipped",
    out_feature_class=r"C:\Users\...\Thiessen_Clipped_Dissolved",
    dissolve_field="ID;NAME",
    statistics_fields=None,
    multi_part="MULTI_PART",
    unsplit_lines="DISSOLVE_LINES",
    concatenation_separator=""
)
arcpy.management.Merge(
    inputs="Thiessen_Clipped_Dissolved;IDN_Kabupaten",
    output=r"C:\Users\...\Regency_borders_offshore",
    field_mappings='ID "ID" true true false 20 Text 0 0,First,#,
    Thiessen_Clipped_Dissolved,ID,0,19,IDN_Kabupaten,ID,0,19;NAME "Name" true true
    false 70 Text 0 0,First,#,Thiessen_Clipped_Dissolved,NAME,0,69,IDN_Kabupaten,
    NAME,0,69;Shape_Length "Shape_Length" false true true 8 Double 0 0,First,#,
    Thiessen_Clipped_Dissolved,Shape_Length,-1,-1;Shape_Area "Shape_Area" false
    true true 8 Double 0 0,First,#,Thiessen_Clipped_Dissolved,Shape_Area,-1,-1;AREA
     "Area in Square Kilometers" true true false 0 Double 0 0,First,#,IDN_Kabupaten
    ,AREA,-1,-1;TOTPOP_CY "2021 Total Population" true true false 0 Long 0 0,First
    ,#,IDN_Kabupaten,TOTPOP_CY,-1,-1;InPoly_FID "InPoly_FID" true true false 0 Long
     0 0,First,#,IDN_Kabupaten,InPoly_FID,-1,-1;SimPgnFlag "SimPgnFlag" true true
    false 0 Short 0 0,First,#,IDN_Kabupaten,SimPgnFlag,-1,-1;MaxSimpTol "MaxSimpTol
    " true true false 0 Double 0 0,First,#,IDN_Kabupaten,MaxSimpTol,-1,-1;
    MinSimpTol "MinSimpTol" true true false 0 Double 0 0,First,#,IDN_Kabupaten,
    MinSimpTol,-1,-1;Shape__Area "Shape__Area" false true true 0 Double 0 0,First
    ,#,IDN_Kabupaten,Shape__Area,-1,-1;Shape__Length "Shape__Length" false true
    true 0 Double 0 0,First,#,IDN_Kabupaten,Shape__Length,-1,-1',
    add_source="NO_SOURCE_INFO"
)
arcpy.management.Dissolve(
    in_features="Regency_borders_offshore",
    out_feature_class=r"C:\Users\...\IDN_Kabupaten_Dissolve,
    dissolve_field="ID;NAME",
    statistics_fields=None,
    multi_part="MULTI_PART",
    unsplit_lines="DISSOLVE_LINES",
    concatenation_separator=""
)
```

10.5.4 Step 4: Intersecting borders with the well data and filtering for development wells

Now, I upload the Excel file to ArcGIS Pro, convert it to point data using the coordinates in the table and assign each point to its respective regencies. Notably, it is in line 4 below where I filter for development wells (and extraction wells in the robustness check):

```
1 arcpy.conversion.ExcelToTable(
2     Input_Excel_File=r"C:\Users\...\EXCEL_FILENAME.xlsx",
```

```
    Output_Table=r"C:\Users\...\Welldrillings_ExcelToTable1",
    Sheet="",
    field_names_row=1,
    cell_range=""
)
arcpy.management.XYTableToPoint(
    in_table="Welldrillings_ExcelToTable1",
    out_feature_class=r"C:\Users\...\Welldrillings_ExcelToTable1_XYTableToPoint",
    x_field="C_x",
    y_field="C_y",
    z_field=None,
    coordinate_system='GEOGCS["GCS_WGS_1984",DATUM["D_WGS_1984",SPHEROID["WGS_1984
    ",6378137.0,298.257223563]],PRIMEM["Greenwich",0.0],UNIT["Degree
    ",0.0174532925199433]];-400 -400 1000000000;-100000 10000;-100000
    10000;8.98315284119521E-09;0.001;0.001;IsHighPrecision'
)
arcpy.analysis.SpatialJoin(
    target_features="Wells",
    join_features="IDN_Kabupaten_Dissolve",
    out_feature_class=r"C:\Users\...\Wells_SpatialJoin1",
    join_operation="JOIN_ONE_TO_ONE",
    join_type="KEEP_ALL",
    field_mapping='FID "FID" true true false 4 Long 0 0,First,#,Wells,FID,-1,-1;
    CATALOGUE_ID "CATALOGUE_ID" true true false 255 Text 0 0,First,#,Wells,
    CATALOGUE_ID,0,254;UWI "UWI" true true false 255 Text 0 0,First,#,Wells,UWI
    ,0,254;LAT "LAT" true true false 255 Text 0 0,First,#,Wells,LAT,0,254;LONG "
    LONG" true true false 255 Text 0 0,First,#,Wells,LONG,0,254;UTM_ZONE "UTM_ZONE"
     true true false 255 Text 0 0,First,#,Wells,UTM_ZONE,0,254;EASTING "EASTING"
    true true false 255 Text 0 0,First,#,Wells,EASTING,0,254;NORTHING "NORTHING"
    true true false 255 Text 0 0,First,#,Wells,NORTHING,0,254;UUID "UUID" true true
     false 255 Text 0 0,First,#,Wells,UUID,0,254;AREA_ID "AREA_ID" true true false
    255 Text 0 0,First,#,Wells,AREA_ID,0,254;AREA_TYPE "AREA_TYPE" true true false
    255 Text 0 0,First,#,Wells,AREA_TYPE,0,254;FIELD_NAME "FIELD_NAME" true true
    false 255 Text 0 0,First,#,Wells,FIELD_NAME,0,254;WELL_NAME "WELL_NAME" true
    true false 255 Text 0 0,First,#,Wells,WELL_NAME,0,254;WELL_CLASS "WELL_CLASS"
    true true false 255 Text 0 0,First,#,Wells,WELL_CLASS,0,254;SPUD_DATE "
    SPUD_DATE" true true false 255 Text 0 0,First,#,Wells,SPUD_DATE,0,254;ALIAS_LN
    "ALIAS_LN" true true false 255 Text 0 0,First,#,Wells,ALIAS_LN,0,254;BA_LN "
    BA_LN" true true false 255 Text 0 0,First,#,Wells,BA_LN,0,254;STTS_TYPE "
    STTS_TYPE" true true false 255 Text 0 0,First,#,Wells,STTS_TYPE,0,254;
    ENVIRONMENT_TYPE "ENVIRONMENT_TYPE" true true false 255 Text 0 0,First,#,Wells,
    ENVIRONMENT_TYPE,0,254;SRFCE_LAT "SRFCE_LAT" true true false 255 Text 0 0,First
    ,#,Wells,SRFCE_LAT,0,254;SRFCE_LONG "SRFCE_LONG" true true false 255 Text 0 0,
    First,#,Wells,SRFCE_LONG,0,254;C_x "C_x" true true false 8 Double 0 0,First,#,
    Wells,C_x,-1,-1;C_y "C_y" true true false 8 Double 0 0,First,#,Wells,C_y,-1,-1;
    NEAR_FID "NEAR_FID" true true false 4 Long 0 0,First,#,Wells,NEAR_FID,-1,-1;
    NEAR_DIST "NEAR_DIST" true true false 8 Double 0 0,First,#,Wells,NEAR_DIST
    ,-1,-1;ID "ID" true true false 20 Text 0 0,First,#,
    IDN_Kabupaten__Crea_Dissolve1,ID,0,19;NAME "Name" true true false 70 Text 0 0,
    First,#,IDN_Kabupaten__Crea_Dissolve1,NAME,0,69;Shape_Length "Shape_Length"
    false true true 8 Double 0 0,First,#,IDN_Kabupaten__Crea_Dissolve1,Shape_Length
    ,-1,-1;Shape_Area "Shape_Area" false true true 8 Double 0 0,First,#,
    IDN_Kabupaten__Crea_Dissolve1,Shape_Area,-1,-1',
    match_option="INTERSECT",
    search_radius=None,
    distance_field_name="",
    match_fields=None
)
arcpy.conversion.TableToExcel(
    Input_Table="Wells_SpatialJoin1",
    Output_Excel_File=r"C:\Users\...\wells.xls",
    Use_field_alias_as_column_header="NAME",
    Use_domain_and_subtype_description="CODE"
)
```

10.5.5 Step 5: Converting well data to regency-year observations

With the newly created file, I now return to Excel Power Query Editor to convert the table into count data:

```
= Table.AddColumn(Source, "Custom", each Text.End([SPUD_DATE], 4))
= Table.TransformColumnTypes(#"Added Custom",{{"Custom", Int64.Type}})
= Table.RenameColumns(#"Changed Type1",{{"Custom", "year"}})
= Table.SelectRows(#"Renamed Columns", each [WELL_CLASS] = "DEVELOPMENT" or [WELL_CLASS] = "Development" or [WELL_CLASS] = "FIELD WELL" or [WELL_CLASS] = "HORIZONTAL" or [WELL_CLASS] = "Horizontal" or [WELL_CLASS] = "INFILL WELL" or [WELL_CLASS] = "Infill Well" or [WELL_CLASS] = "Outpost Well")
= Table.Group(#"Filtered Rows", {"NAME", "year", "ID"}, {{"Count", each Table.RowCount(_), Int64.Type}})
= Table.ReorderColumns(#"Grouped Rows",{"ID", "NAME", "year", "Count"})
```

After loading and saving this file, the data is now properly formatted for use in this study.

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