Incomplete Regulation and Spatial Equilibrium in the Offshore Oil and Gas Industry

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Abstract

How effective is local regulation when production occurs in a global market and capital is mobile? When environmental regulations differ between regions capital may relocate, resulting in spatial misallocation and 'leakage' of pollution and profits. In this paper I build an empirical framework to study incomplete regulation in a decentralized capital market, where capital is mobile and production occurs across multiple locations. The model extends the spatial location-choice and matching literature in industrial organization to accommodate two-sided vertical firm heterogeneity. Using novel contract and location data, I apply the framework to the global market for deepwater oil rigs. Offshore rigs are marine vessels that move around the ocean drilling wells, matching with oil companies like BP and Chevron to produce wells. Local changes in drilling standards and other regulations spur equilibrium rig relocation. The main policy finding is that incomplete regulations, such as unilateral increases in drilling standards, cause large shifts in profits and (expected) oil spilled to other markets through the capital relocation channel. In contrast, I find that more complete regulation - like a coordinated global agreement on drilling standards - would be significantly more effective than uncoordinated policies.

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1 Introduction

Regulation is often incomplete because it is specific to a certain geographical area. When physical capital can move location to escape the regulation it can result in spatial misallocation and 'leakage' of pollution. Despite large literatures that study incomplete regulation at an aggregate or theoretical level, much less in known about the effects in specific settings, and the exact mechanisms by which incomplete regulation distorts the geography of production.[1] Data and measurement challenges have frustrated progress. For instance, countries vary in how they measure pollutants and capital.[2] Furthermore, granular data about inter-firm contracts, prices, and relationships - which are important to disentangling misallocation from unobserved factors - are often confidential.

In this paper I answer the question: how effective is local regulation when production occurs in a global market and capital is mobile? To do so I build an empirical framework of incomplete regulation in a decentralized capital market, where buyers and sellers need to match with each other to produce output and production occurs across multiple locations. The framework extends the spatial location choice and matching literature in industrial organization to accommodate two-sided vertical heterogeneity.[3] I estimate the framework using novel data on contracts and daily status updates for the universe of deepwater drilling rigs worldwide. The availability of unusually detailed contract data for a global capital market, as well as the fact that the physical production of oil and the rigs themselves are relatively comparable across locations, allows me to overcome many of the data and measurement difficulties that are often present when studying capital markets. I use the estimated model to evaluate how common policies affect profits, oil spilled, and total welfare, through *matching and capital relocation*.[4]

[1] Some exceptions include Fowlie et al. (2016) which studies the cement industry, Abito et al. (2020) which studies electricity markets, and Hsiao (2021) which studies the market for palm oil. Unlike these studies which focus on long-run investment decisions, this paper highlights how incomplete regulation operates through the capital relocation channel in a decentralized factor market.

[2] For a detailed discussion about measurement challenges in assessing leakage risk see Fowlie and Reguant (2018). For a more detailed discussion about the implications of capital mismeasurement see Collard-Wexler and De Loecker (2016).

[3] Previous work has focused on markets where agents are relatively homogeneous like Bulk Shipping (Brancaccio et al. (2020)) and Taxis (Buchholz (2020)).

[4] My results measure inefficiency from the perspective of a global social planner who considers total global barrels spilled and global total profits.

The international offshore oil and gas industry is an excellent setting in which to study incomplete regulation in a capital market. It is an archetypal global dirty industry with patchwork environmental regulation (such as the 2010 offshore drilling moratorium in the US) and an easily movable form of capital: drilling rigs. The industry is decentralized and oil companies such as BP and Chevron do not own the capital required to drill oil and gas projects. Instead, they contract out drilling to a rig owner. The market is shaped by space: oil field locations are situated across the world and rig owners must choose the best location for their capital. It is also shaped by vertical heterogeneity in capital types and drilling projects: rigs can be ranked by their *efficiency* (their on-board drilling technology) and oil and gas projects can be ranked by their *complexity*. The match complementaries matter, with more efficient rigs suited to drilling more complex projects.[5]

Two key features make this capital market particularly responsive to incomplete regulation. First, offshore oil rigs are classified as 'marine vessels' and are explicity designed to be easily movable between locations. This allows rig owners to quickly respond to differences in demand and regulatory conditions. Second, the deepwater segment of the offshore oil and gas industry is somewhat 'under-supplied'.[6] Therefore, entry of displaced rigs to a new location tends to significantly increase the number of wells drilled, and as a result oil production and the number of barrels of oil spilled.

In this market, a change in the relative regulation between two locations - for example, a change in standards or a moratorium on drilling only in the US market - generates inefficiency through two channels from the perspective of a global social planner. First, rigs choose to relocate to countries without the new regulation, rather than remain in countries which contain projects that are the most productive matches, resulting in spatial misallocation. Second, the relocation of capital to countries without the new regulation causes more drilling projects to be undertaken in those markets, resulting in an increase in the likelihood of an oil spill and potentially undercutting the benefits of the regulation.

[5]Note that in the paper I use the terms 'capital' and 'rig' interchangeably. Similarly, I use the terms 'project' and 'well' interchangeably.

[6]For example, some rig types experience nearly full utilization. One might ask why these supply constraints do not induce rig entry, thereby relaxing the constraints. A possible reason is that non-utilized time is highly costly to rig owners - they will typically need to pay expenses for a full crew which can amount to hundreds of thousands of USD/day, but without the income of a drilling contract. Hence, even small amounts of non-utilized time can make new rig entry unprofitable.

I begin with an analysis of the 2010 US offshore drilling moratorium, which was active in the months after the Deepwater Horizon/BP oil spill in the US Gulf of Mexico. I focus on the effects on the deepwater segment of the drilling market. The 2010 moratorium was a particularly stark example of incomplete regulation: while drilling was temporarily banned in the US market, it was not banned in other locations around the world. The data show that rig owners responded to this difference in regulation by temporarily relocating out of the US market and to markets without the ban where they could continue to drill like Mexico, West Africa, and Brazil. As the moratorium was lifted and permitting slowly returned to its previous level, rigs then relocated back the the US Gulf of Mexico.

Motivated by this illustrative example, I estimate a model of the global deepwater drilling market using data on 6503 status updates (including data on contracts) of all deepwater rigs worldwide between 2005-2016. In the structural model there are several spatial locations worldwide (oil fields). Locations differ by demand (potential projects), as well as drilling costs, which are dependent on the severity of the environmental regulation and geological factors. Within each location oil companies contact rigs to undertake projects, and - given the types of available rigs and relative prices in the location - target the type of rig that best matches with their well type.[7]

Turning to the supply side of the model, capital owners are forward-looking. Within a location they may be contacted by an oil company to undertake a contract, in which case they will be unable to match for the duration of the contract. If the rig is not currently in use, it can move to a new location looking to match with a new project or stay in the current location. I view and model this relocation decision in a similar way to a vacant taxi choosing which neighborhood to move to in Manhattan (as in Buchholz (2020)). A key difference, however, is that the presence of two-sided heterogeneity implies that rig owners need to take into account the quality of potential matches for their particular rig type in each location. For instance, high-efficiency rigs are best suited to matching with complex projects, and so the rig owner might prefer to relocate to a region where there are many complex projects (as well as low drilling costs). Aggregating these individual relocation decisions to the global market results in rich equilibrium dynamics, featuring both reallocation of capital across markets and reallocation of matches within locations across capital types.[8]

[7] In equilibrium, the two-sided vertical heterogeneity in this market results in complex wells targeting high-efficiency rigs and simple wells targeting low-efficiency rigs.

[8] I detail these dynamics in Section 4.5.1.

I use the model to test several counterfactual policies. First, I consider a unilateral increase in drilling standards in the US market from the status quo to the more stringent 'North Sea standards' that are present in Europe. I show how the capital relocation channel - combined with the fact that rig supply is relatively constrained across the globe - induces substantial leakage in the number of barrels spilled and where oil is produced. Specifically, for every barrel of oil not spilled in the US market, 0.48 barrels are spilled elsewhere. Similarly, for every \$1 of profit lost in the US, \$0.45 is generated elsewhere in the world. Overall, unilateral action would increase global welfare by 3.2%, which is much less effective that implementing the regulation in a 'no relocation world' benchmark, which would increase global welfare by 11.8%.

I next consider the effects of a coalition of 'richer countries' (which incorporates the US, Australia, and countries in South America) who undertake a coordinated increase in standards. This decreases leakage compared to the unilateral action counterfactual but nevertheless results in a global social welfare increase of only 4.3%; in the absence of leakage the regulation would be much more effective and lead to an increase in social welfare of 18.3%. In addition, this coalition results in leakage of pollution to poorer countries, raising concerns around the equity of environmental outcomes. I also consider a proposed global agreement on safety standards. This largely eliminates leakage and results in a total welfare increase of 25.3%, around as effective as implementing the regulation in the 'no relocation' benchmark (28.2%). Taken together, the results quantify and highlight the effectiveness of a global agreement on standards in the oil and gas industry as compared to more fragmented or unilateral policies.

Finally, I show that a simpler model without two-sided vertical heterogeneity would fail to capture disproportionate relocations of high-efficiency capital which tend to drill complex wells. Therefore, this simpler model would under-predict overall leakage and therefore overstate the welfare effects of counterfactual patchwork policies. In other words, it is important to account for not just *how much* capital will leave after a change in regulation, but also *what types* of capital will leave.

Overall, this paper makes three main contributions. The first is a novel dataset of firm-to-firm contracts, status updates, and projects, in a global capital market. The second contribution is a new framework of location-choice and matching in a decentralized capital market which allows for two-sided vertical heterogeneity. The third main contribution is a set of new findings about the efficacy of incomplete regulation in one of the world's largest economic sectors: the offshore oil and gas industry.

Related literature This paper is related to several strands of literature. The first is the literature on incomplete environmental regulation. For example, recent work has looked at incomplete environmental regulation in the cement market (Fowlie et al. (2016)) and electricity markets (Abito et al. (2020)). In contrast to these papers which focus on long-run entry, exit, and investment decisions, this paper focuses on short-run contracting and relocation decisions in a decentralized capital market.

A second strand of literature is in international trade where many papers investigate the relationship between environmental regulation and the patterns of trade. Most notably, these papers seek to test the 'pollution haven hypothesis' which is that stringent regulation in developed countries like the US has caused industries to relocate to less regulated developing countries (see Copeland and Taylor (2003) for a summary). Overall, the literature has found mixed evidence for the pollution haven hypothesis, detecting effects in more 'footloose' industries e.g. Ederington et al. (2005). Complementary to these studies which use more aggregated data across industries, in this paper I study a particular 'footloose' industry where more granular data are available to delve into a particular mechanism by which industries can move location (capital relocation), and where the patterns of relocation in response to environmental regulation are a first-order concern to the industry.

A third strand is research into the oil and gas industry. For example, Kellogg (2011) uncovers relationship-specific learning between onshore production companies and drilling contractors. A literature studies the effects of regulation on this important industry (e.g. Lewis (2019) studies how patchwork regulation distorts drilling decisions in the onshore oil and gas industry in the US). The papers Corts (2008) and Corts and Singh (2004) work with a more aggregated version of offshore rig data for a different period of time, and these data contain fewer covariates for the projects undertaken under each contract. Vreugdenhil (2020) uses contract data in the US Gulf of Mexico to study how booms and busts affect mismatch in the shallow water market; this paper uses similar contract data but in the global *deepwater* floater market, focusing on capital relocation between oil fields in response to regulation but similarly accounting for misallocation from mismatch between well types and rig types.

A fourth strand of literature studies how place-based tax and subsidy policies shape the distribution of firms e.g. Fajgelbaum et al. (2018). In this literature, Gaubert (2018) builds a general equilibrium model that stresses the importance of sorting between firm efficiency and city size in predicting firm location decisions and the equilibrium city size distribution. This paper differs by focusing on short-run relocation and contracting choices in a framework suited to studying a decentralized capital market.

Finally, this paper is related to a recent literature that estimates spatial matching models in industrial organization (Frechette et al. (2019), Buchholz (2020), Brancaccio et al. (2020)). Unlike these papers, which focus on markets like taxis and bulk shipping where agents are relatively homogeneous, this paper differs by providing a framework that can also incorporate vertical heterogeneity in firms.

2 Market description and data

2.1 Market description

Offshore drilling is segmented into shallow water drilling (wells at less than 500ft water depth in places like the outer-continental shelf in the US Gulf of Mexico) and deepwater drilling (wells situated in greater than 500ft of water depth). I follow standard industry practice and treat these two segments as separate markets due to the differences in capital types, geographical locations, and the scale of engineering required to drill a well. In this paper I focus solely on the deepwater drilling segment of the industry. Due to the extreme water depths deepwater wells are drilled by 'floater' drilling rigs (called either Semi-submersibles or Drillships) which float on the ocean's surface and are anchored to the well site. This is in contrast to the shallow water market detailed in Vreugdenhil (2020) where the wells are drilled by Jackup rigs which extend their legs to the seabed.

The process of drilling a deepwater well and procuring a rig is as follows. Oil companies like BP and Chevron lease squares of the seabed from national governments which provide them the option to drill a well. Using geological surveys and (if available) information about other existing wells in nearby leases, these oil companies decide whether to drill a well and determine the potential well design. I detail later exactly how to quantify well designs into a well complexity index. Since oil companies do not own the oil rigs they use to drill with, upon deciding to drill a

Figure 1: A deepwater drilling rig

Note: This picture shows a deepwater drilling rig (called the 'Deepwater Nautilus') undergoing a dry tow between locations. Source: https://2b1stconsulting.com/wp-content/uploads/2012/04/nautilus-dry-tow.jpg.

well they need to match with an appropriate drilling rig given the complexity of a potential well design. I explain in the model section exactly how this matching takes place. Oil rigs are rented under simple dayrate contracts for the time it takes to drill a well.[9] After the well is completed (around 6 months) it is typically connected to an undersea pipe for continuing extraction and the rig moves on to its next job. Oil companies are responsible for the well design while rig owners are responsible for ensuring the rig's equipment is in working order, labor costs etc. The oil company has a representative (called the 'company man') who lives on the rig and represents the oil company's interests.

Oil rigs are ships that move around the ocean drilling wells. Since oil wells are in different locations drilling rigs are designed to be easily movable. Long-distance moves between fields

[9] An alternative contracting form is sometimes used in the industry: a turnkey contract where a rig is hired to drill a set number of wells rather than for a period of time Corts and Singh (2004). I have additional data from IHS on whether a contract is a turnkey or dayrate contract for the US market. In the period of time studied, for the deepwater market, all of the contracts are dayrate contracts (interestingly, as I mention in Vreugdenhil (2020), turnkey contracts are relatively rare after the year 2000 for the US Jackup market as well). Further there is no reason to suspect that firms use turnkey contracts in the non-US markets.

(for instance, from the US Gulf of Mexico to the North Sea) are usually undertaken using a 'dry-tow' where the rig is manoeuvred onto a special ship and this ship then transports the rig. An example of a deepwater oil rig moving using a dry tow is in Figure 1.

2.2 Data

The contract and status data comes from a proprietary dataset from Rigzone (an industry data provider). The full dataset consists of the status of marketed drilling rigs worldwide 2000-2016. I cut the data to only deepwater rigs (defined as those with a maximum drilling depth of >500 feet). I observe the country and region that each drilling rig is currently in at each point in time, and whether a rig is idle or currently under contract. If a rig is under contract then I observe key covariates for the contract including price, duration, and the oil company who owns the well. Contracts are almost always fixed price for a given duration and rarely contain performance incentives. In addition, in the US Gulf of Mexico, for a subset of the contracts I also have data on the exact projects that are undertaken under each contract (which are publicly available from the regulator - the BSEE), and these can be combined using an engineering model to determine the complexity of the well which is an important consideration for which rig to use. I detail steps taken to clean the data, construct the matched subset of contracts, and build other metrics, in the Appendix.

I use data in the years 2005-2016 in the sample. I choose this period because - in contrast to the shallow water rig segment of the market - the total number of contracts drilled each year is relatively stable and does not appear to respond to large cyclical changes in oil and gas prices over this time (in the Appendix I plot the number of contracts executed globally per year in Figure 8). Motivated by this fact I choose to model the market as in a steady-state equilibrium without aggregate shocks. Although most rigs operate under relatively short-run contracts (e.g. 6 months) and are rented over time by many different oil companies there is a small number of rigs that operate continually under very long-term contracts. I delete these rigs (specifically, those that operate under long-term contracts of more than 2 years). In total I have 6503 status updates for deepwater rigs.

As is the convention in the industry, rigs can be ranked by their maximum drilling depth which is a proxy for capital efficiency since it is highly correlated with onboard technology, age etc. I aggregate capital heterogeneity into three types by maximum drilling depth and call these types

Table 1: Summary Statistics

Variable	Rig Type	N	Mean	Std. Dev.
Status Updates (unique)	All	6503		
Contract Price (millions of USD/day)	All	1740	0.34	0.15
	Low	879	0.28	0.12
	Medium	455	0.33	0.14
	High	406	0.47	0.13
Contract Duration (days)	All	1740	186	160
	Low	879	171	148
	Medium	455	200	165
	High	406	203	174
Prob. of Relocation	All	1343	0.38	0.24

Note: This table contains summary statistics for the worldwide market for deepwater drilling rigs in the sample. Status updates are the number of changes to a rig status in the data (these are updated daily but rigs may remain in the same status - e.g. undertaking a particular contract - for many months). Price is the daily contract rate paid by an oil companies to the capital owner. Duration is the length of the contract in days.

'low', 'medium' and 'high' specification rigs.

Table 1 shows that high-specification rigs fetch higher prices ($0.47 million/day) than mid-specification rigs ($0.33 million/day) and low-specification rigs ($0.28 million/day). Table 1 also shows that all capital types operate under similar length contracts (with a median duration of around six months).

I aggregate capital locations into eight large regions across the world: (West) Africa, Asia, Australia, Central Americas, Europe, Middle East, South America, and the US. Within these regions the main oil fields are relatively close to each other.

I have additional data in the US market from the regulator (the BSEE) about the exact projects undertaken under a subset of contracts. I aggregate projects up into a one-dimensional index of project complexity using an engineering model used in the industry called the 'mechanical risk index'. This index takes elements of the well design (e.g. number of casings, depth, bottomhole pressure) into a complexity score and higher scores indicate more difficult projects to drill (which I later show, are best undertaken by high-specification rigs). I follow Vreugdenhil (2020) where I build the mechanical risk index for shallow water projects (further details about the index are also in this paper).

Finally, I use an engineering model that is used by the US regulator to map production into the expected barrels of oil spilled under different regulatory scenarios. A full description of this model is in Appendix A.

3 Descriptive analysis of the market for deepwater rigs

To motivate the model I make several observations of the raw data.

Observation 1: Rigs respond to differences in regulation by changing location.

To make this observation, I analyze the effects of the 2010 offshore drilling moratorium as a case study.[10] On April 20 the Macondo prospect that the Deepwater Horizon oil rig was drilling blew out, discharging oil into the Gulf of Mexico in the largest oil spill in US history.[11] On April 29 the Obama administration announced it would issue no new drilling permits until an investigation was completed and I date the start of the moratorium from this date. Later, a continuation of this moratorium was introduced in May 30 2010. Although the moratorium officially ended in October 2010 a 'defacto moratorium' persisted until at least February 2011 with no new drilling permits awarded (Broder and Krauss (2011)).

Market analysts predicted rig relocation as a consequence of the moratorium. For example, in May 2010: *"[The rigs] cost 500,000 to 1 million a day to lease, says Michael King of FMC Technologies in Houston. He presumes many of their owners will break their contracts and ship them to places with ongoing demand. "There are oil fields off West Africa, off Brazil and in the North Sea," he said. That might be the most efficient use of a rig over the next six months."* (Ludden (2010)). I confirm this logic in Figure 2.

Figure 2(a) plots the short-run effects of the moratorium focusing on rig utilization (the proportion of rigs that are actively drilling). The moratorium had a dramatic effect on rig utilization, causing it to fall from around 95% to 20% (it is difficult to safely stop all drilling and so some rigs continued to drill). Over time, through rig exit and a slow return of permitting, utilization climbs to its pre-moratorium level.

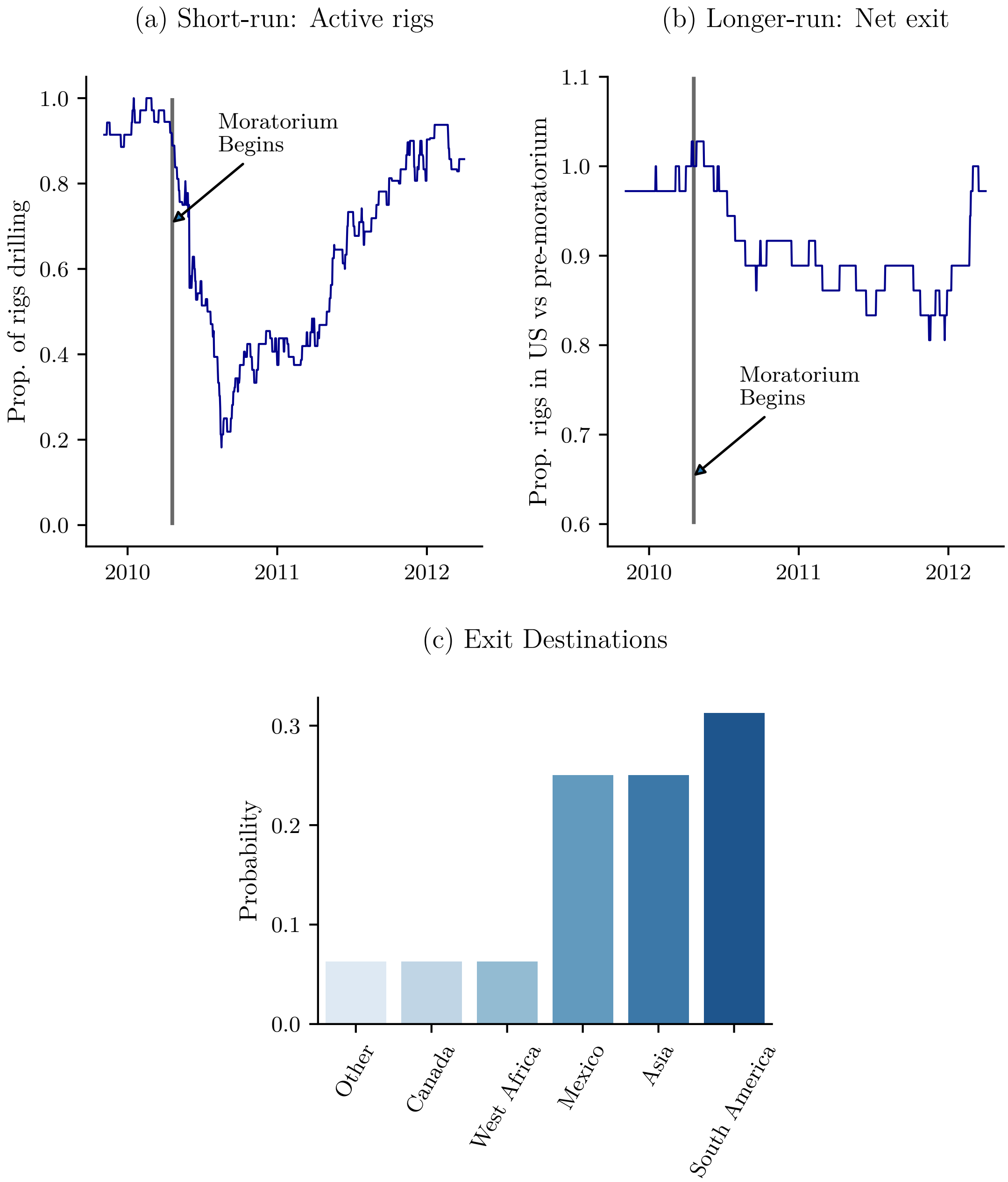
Figure 2(b) plots the cumulative change in the number of drilling rigs in the Gulf of Mexico. After the moratorium is implemented rigs quickly exit for other oil fields not under a moratorium where they will be more fully utilized. When the moratorium is lifted and permitting returns to its previous rate, rigs reenter the region. Overall, this evidence shows that rigs are responsive to differences in regulation across markets.

Figure 2(c) plots the locations to where rigs exited after the moratorium. The locations that rigs exit to are predominantly locations that are close to the US Gulf of Mexico: the Mexican portion

[10] Note that my main analysis incorporates information of *all* movements of rigs worldwide over a longer period of time to test the effects of regulation.

[11] Deepwater Horizon was owned by Transocean and was drilling a well for BP.

Figure 2: Effects of the 2010 moratorium on the market for deepwater drilling rigs



Notes: For part (a) and (b) I indicate when the moratorium started. However, I do not plot where the moratorium ended since the exact date is hard to determine: although the moratorium officially ended in October 2010, a ‘defacto’ moratorium persisted where no permits were awarded for new wells until February 2011. The permit approval slowdown ended around mid-2011. Part (c) shows the destinations of the rigs that exited after the 2010 moratorium.

of the Gulf of Mexico, West Africa, Brazil, and Canada. In the industry, these locations (plus the US market) are known as the 'golden triangle' of deepwater drilling (Odell et al. (2013)). This suggests that distance is an important factor behind how rigs make their location choice.

Observation 2: There is two-sided heterogeneity in this market, and positive sorting patterns suggest that the quality of match matters.

Figure 3 illustrates that sorting patterns between rigs and projects in the US market.[12] Recall that we can rank vertically by their complexity using an engineering model called the 'mechanical risk index' and we can also vertically rank rigs by their efficiency (proxied by their maximum drilling depth). The findings illustrate that more complex projects tend to match with more efficient rigs, both on average in Figure 3(a) and over the entire distribution of project types Figure 3(b).[13] These pictures suggest that match complementaries matter and motivate that two-sided heterogeneity is an important element to include in the model. Different markets have different distributions of well complexity, which make them more or less suitable for relocating different types of rigs.

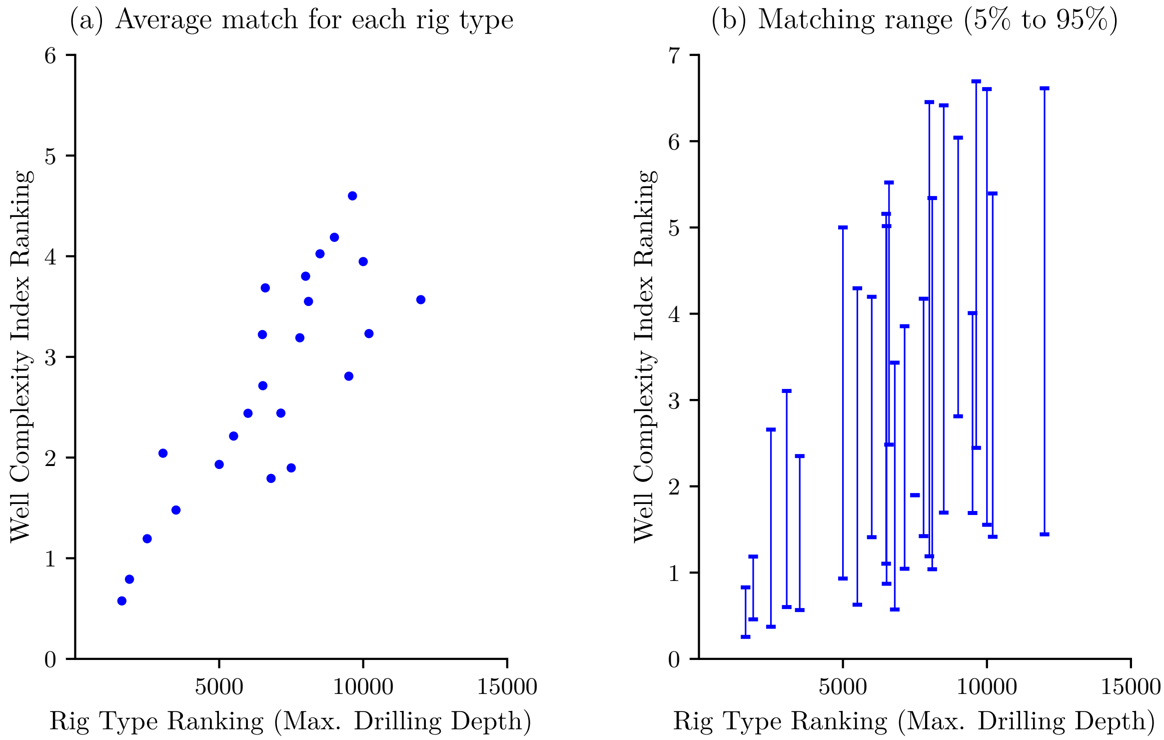
Observation 3: High-specification capital tends to relocate more frequently, and has higher utilization and prices.

I document further differences between the capital types in Table 2. In the first row I break out the probability of relocation by each capital type. Comparing the probability of relocation across types, high-specification rigs are much more likely to relocate when they are unmatched than lower specification rigs. This element is a key factor why a simpler model without two-sided heterogeneity may fail to accurately predict the effects of regulation. Specifically, higher-specification rig types tend to disproportionally relocate compared to other types of rigs after a change in regulation. As I explain further in the counterfactuals section, where I perform an exercise that shuts down two-sided heterogeneity, in equilibrium this disproportionally shifts the drilling of complex wells across locations, which tends to increase leakage of pollution and

[12] I can construct project complexity from permit data from the US regulator. However, detailed information on the projects undertaken outside the US are not available.

[13] These sorting patterns are also apparent for shallow-water rigs Vreugdenhil (2020).

Figure 3: Sorting patterns for deepwater rig efficiency vs project complexity



Notes: For both figures, the x-axis is the rig efficiency ranking (where rig efficiency is proxied for by the maximum drilling depth) and the y-axis is the project complexity ranking (the 'mechanical risk index' which is an engineering model used in the industry that maps well covariates into a one-dimensional index for how difficult the well is to drill). Each point on the x-axis corresponds to a particular maximum drilling depth. These maximum drilling depths are typically given as round-number increments (e.g. maximum drilling depth of 6000 feet) and so each point on the graph corresponds to all the projects undertaken by the many rigs which share a particular drilling depth. Figure (a) presents positive sorting patterns in terms of the average match for each rig type. Figure (b) presents positive sorting patterns in terms of the entire distribution of projects that rigs match to.

Table 2: Documenting differences between capital types

Metric	Capital Type		
	Low	Mid	High
Prob. of relocation	0.25	0.3	0.7
Utilization	0.89	0.89	0.95
Dayrate	0.28	0.33	0.47

Note: This table documents differences between the three aggregated rig types. The row 'prob. of relocation' refers to the probability that an unmatched rig chooses to relocate to a different location vs stay in the current location. The row 'utilization' refers to the proportion of time a rig is under contract. The row 'dayrate' is the average price per day to rent a rig in millions of USD.

profits compared to a model where rigs are homogeneous. Differences in leakage then lead to different welfare conclusions.

Table 2 also shows that high-specification rigs tend to fetch higher prices and have higher utilization rates than low and mid-specification rigs. These differences may occur due to two reasons and the model in the next section can account for both. First, high-specification rigs may have a competitive advantage in drilling many types of wells, which leads them to be used more and receive higher prices. Second, the higher frequency of relocation implies that high-specification rigs are quick to leave a low utilization location and also receive higher prices due to a higher outside option.

4 Model

4.1 Setup

There are locations $l \in L$ across the world, each of which corresponds to an oil field. Agents are projects (wells) x and capital (rigs) y. Capital is differentiated by efficiency $y \in Y = \{low, mid, high\}$ and projects are differentiated by their complexity x. The model is dynamic with one period equal to one month. Agents have the discount factor β. In order to drill a project, a project owner needs to match with capital. Each rig has a backlog of projects and if the backlog is sufficiently short (specifically, if the number of contracted months in the backlog is below a critical value $t_{backlog}$) then the rig is 'available to match'.[14] The timing in each period within each location l is as follows:

1. Project entry in each location The number of new potential projects in each period is given by a draw from a poisson distribution with location-specific mean. The type of each of these potential projects is characterized by a draw from a distribution $x \sim f_l^{entry}(.)$ of project complexity.

2. Targeting Each potential project observes whether a rig is 'available' (i.e. whether its backlog is below $t_{backlog}$) and chooses which type of available rig to attempt to match with ('target'). If there are less available rigs of a certain type than projects attempting to match then matches are allocated randomly and unmatched potential projects immediately exit.[15] If there are more available rigs of a certain type than projects targeting that type then matches are allocated randomly within a rig type.

3. Matching If a potential project successfully matches with capital the τ periods of the contract are added to the capital's backlog. The total per-period payoff is given by $m(x, y) - c_{l,y}$ for each of the τ periods of the contract, where the function $m(x, y)$ is the match value and $c_{l,y}$ is a location-specific and capital type-specific cost.[16] Prices are determined by Nash bargaining.[17]

4. Relocations Capital not currently under contract can either stay in the current location

[14]The constraint that projects will refuse to match if the backlog is too long arises mainly from oil company preferences; rig owners tend to prefer longer backlogs since it reduces the risk of a rig not being utilized. In fact, it is common for rig owners to actively advertise their deepwater rig backlogs to shareholders in annual reports as a positive signal about their firm's financial health.

[15]The immediate exit of unmatched potential projects is not an assumption but rather optimal behavior given the setup of the problem. Specifically, if a potential project is unmatched it implies that there is not enough available capital (i.e. matching with any capital would produce a backlog longer than $t_{backlog}$). But then this implies that waiting an additional period for capital to become available would require waiting longer than $t_{backlog}$ to drill a well.

[16]The cost $c_{l,y}$ incorporates both costs from differences in oil field geology and from regulation. These costs are operating expenses borne by the capital owner.

[17]For example, Corts and Singh (2004) mention that each contract is "ultimately negotiated independently; there is no "market" in which firms act as price takers".

l, or to move to a new location l'. Moving to a different location incurs a cost that is dependent on distance between locations $d_{l,l'}$ but not capital type.[18]

For this paper, I abstract from any worldwide entry (i.e. building new rigs) or worldwide exits (cold-stacking or scrapping rigs).

Discussion of key assumptions Before getting into the details of the model, I now discuss and defend two key assumptions. First, I assume that agents make their decisions based on long-run averages in the market (specifically, for potential projects, they use the long run average probability that a rig type is at the capacity constraint to determine rig selection and prices, and rigs use long-run averages for the probability of matching and prices in their location choice). As previously mentioned, I do not allow for aggregate oil price shocks. However, a steady state assumption is still in contrast to an alternative set-up where agents can condition their behavior on a more transient state of the market (such as exactly how many other potential projects entered in the same period, or the exact number of months in the backlog of every rig). The benefit of this assumption is computational; allowing agents to condition their behavior on a more transient state of the market would add substantial complexity to the decisions of potential projects and capital, and generate a large state space for capital's dynamic decisions, which would result in a curse of dimensionality.

In addition, this assumption is arguably realistic for this market. For example, from the point of view of one oil company, the exact investment decisions of other oil companies (i.e. the number of other potential projects) is not precisely known at any one point in time. Oil companies may delay announcing new drilling projects to avoid nearby exploration from competitors. For my data provider, contracts are eventually fully reported but there is often a delay, so the data are somewhat 'stale' and the exact state of the marketplace is unknown.

The second notable assumption is that I assume that agents can target their best match, and do not allow for information or coordination frictions in matching.[19] This assumption significantly

[18]Typically long-distance moves are accomplished using tow boats, not the internal engine on board the capital, and so I do not allow moving costs to depend on the capital type y.

[19]To some extent, the fact that agents only make decisions based on long-run averages does introduce an inefficiency which could be mitigated by better information, but I do not allow for any frictions beyond this nor is the aim of this paper to investigate counterfactual policies to reduce this inefficiency.

simplifies the demand-side of the model, but stands in contrast to other markets like taxis, bulk-shipping, second-hand aircraft, and the shallow-water jackup rig market in the US Gulf of Mexico, which involve matching with much larger numbers of agents searching on both sides of the market, which leads to coordination frictions. Unlike these markets, the scale of the deepwater rig market is much smaller (for example, some locations may only see a few new matches per month) and so matching arguably involves far fewer opportunities for coordination frictions. Instead, in the model, capital unemployment is generated solely due to the poisson draws in demand: several successive low draws may result in rig unemployment.

4.2 Demand: How projects match with capital

The number of potential projects in each period is drawn from a poisson distribution with mean λ_l. The type of each of these potential projects is given by an iid draw from a distribution $x \sim f_l^{entry}(.)$. These projects contact the type of capital which provides them with the highest expected value. If there are more potential projects than available capital of a certain type, then the market hits a capacity constraint and matches are allocated randomly. To summarize, the only choice that potential projects make is which type of capital to target.

4.2.1 Targeting decision

I now discuss the rig selection process for each potential well. I assume that a well can target its best match.[20] The ex-ante payoff to targeting a capital of type y is:

$$\Pi_l^{project}(x,y) + \epsilon_y = q_{l,y}^{project} \underbrace{\sum_{s=0}^{\tau-1} \beta^s (m(x,y) - p_l(x,y))}_{\text{Value to matching with type } y \text{ capital}} + \epsilon_y \tag{1}$$

[20]The model outlined in this section is a relatively simple version of how rigs are selected in practice. In practice, oil company engineers will determine the well type, write up the details in a a request for quotation, and initially solicit rigs. The rig selection process rarely ends there: offshore rig companies stress that the process of obtaining an offshore rig can be relatively unstructured, with back and forth discussions and negotiations between the parties and that ultimately "our contracts to provide offshore drilling services are individually negotiated" Transocean (2015). Since my dataset only contains data on the eventual outcomes of this process and no information about interim discussions, the model in this section is a simplified reduced form of how this process occurs in practice, ending with one rig ultimately selected and negotiated with.

The term $q_{l,y}^{project}$ is the long-run probability of matching capital type-y in location l (and $1 - q_{l,y}^{project}$ is the probability that capital is at its capacity constraint), $m(x, y)$ is the value of a match between project type x and capital type y, and ϵ_y is an idiosyncratic error for each capital type y distributed iid extreme value. A potential project contacts the capital type that offers it the highest expected value:

$$\max_y \left\{ \Pi_l^{project}(x, y) + \epsilon_y \right\} \tag{2}$$

and integrating over demand $f_l(x)$ the share of potential wells that target capital type y is:

$$s_{l,y} = \int \frac{\exp[\Pi_l^{project}(x, y)]}{\sum_{k\in\{low,mid,high\}} \exp[\Pi_l^{project}(x, k)]} f_l^{entry}(x)dx \tag{3}$$

Since agents can target their best match, I assume that no matches are rejected. I compute the long run probability of matching $q_{l,y}^{project}$ that results from the above targeting decision using a matching simulation detailed in Appendix C.2.[21]

4.3 Supply: Location decision

The location decision of an unemployed capital of type y is to either stay in the same location l, or to choose to move to a different oil field l'.[22] Mathematically, this choice is:

$$\max \left\{ \max_{l' \neq l} \left\{ -c_d d_{l,l'} + \beta V_{l',y} + \sigma_\epsilon \epsilon_{l'} \right\}, b_{stay} + \beta V_{l,y} + \sigma_\epsilon \epsilon_l \right\} \tag{4}$$

Here the first term is the value of moving from location l to l', where c_d is the per-mile transport cost, $d_{l,l'}$ is the distance, $\epsilon_{l'}$ is the idiosyncratic logit error, and σ_ϵ is the scale parameter of the errors. The second term is the value of staying put in location l. In this term, b_{stay} is a parameter that reflects unobserved benefits of remaining unmatched in the same location such as labor savings.

[21] Note that this rig selection choice implicitly assumes that projects will immediately match with rigs if the rig is not at a capacity constraint. I experimented with a more complicated model for rig selection and prices where potential projects discount rig types based on the average delay due to backlog. The results were relatively unchanged and so I choose to not incorporate this more complicated feature.

[22] This section is similar to the setup in Brancaccio et al. (2020).

The value function $V_{l,y}$ (the value of being in location l before matching has taken place) is given by:

$$V_{l,y} = q_{l,y}^{capital}\Big(\sum_{s=0}^{\tau-1}\beta^s(\bar{p}_{l,y} - c_{l,y}) + \beta^\tau V_{l,y}\Big) + (1 - q_{l,y}^{capital})U_{l,y} \tag{5}$$

Here, $q_{l,y}^{capital}$ is the long-run average probability that capital of type y matches with a well in location l. The term $\bar{p}_{l,y}$ is the average price in location l for capital type y.[23]

Using the location decision I can write the value function for unemployed capital:

$$U_{l,y} = \sigma_\epsilon \log\left(\sum_{l'\neq l}\exp\left(\frac{-c_d d_{l,l'} + \beta V_{l',y}}{\sigma_\epsilon}\right) + \exp\left(\frac{b_{stay} + \beta V_{l,y}}{\sigma_\epsilon}\right)\right) + \sigma_\epsilon \gamma^{euler} \tag{6}$$

where γ^{euler} is Euler's constant. I can also write out the choice probabilities of moving to different locations. These choice probabilities are:

$$P(l'|l,y) = \frac{\exp\Big(\big(-c_d d_{l,l'} + \beta V_{l',y}\big)/\sigma_\epsilon\Big)}{\exp\Big(\big(b_{stay} + \beta V_{l,y}\big)/\sigma_\epsilon\Big) + \sum_{l'\neq l}\exp\Big(\big(-c_d d_{l,l'} + \beta V_{l',y}\big)/\sigma_\epsilon\Big)} \tag{7}$$

$$P(l|l,y) = \frac{\exp\Big(\big(b_{stay} + \beta V_{l,y}\big)/\sigma_\epsilon\Big)}{\exp\Big(\big(b_{stay} + \beta V_{l,y}\big)/\sigma_\epsilon\Big) + \sum_{l'\neq l}\exp\Big(\big(-c_d d_{l,l'} + \beta V_{l',y}\big)/\sigma_\epsilon\Big)} \tag{8}$$

4.4 Prices

Since prices are determined by Nash bargaining, the price of an (x, y) match in location l is $p_l(x, y)$ which is determined by:

$$\begin{aligned}\underset{p}{\text{argmax}}&\left[\sum_{s=0}^{\tau-1}\beta^s[m(x,y) - p] - \beta(1-\mathbb{P}_{exit})W_{l,x,y}\right]^{1-\delta}\\ &\times\left[\sum_{s=0}^{\tau-1}\beta^s[p - c_{l,y}] + \beta^\tau V_{l,y} - U_{l,y}\right]^{\delta}\end{aligned} \tag{9}$$

[23] As mentioned, I assume agents make decisions based on long-run market averages. I compute the matching probabilities $q_{l,y}^{capital}$ by simulation and this simulation implicitly takes into account contract backlog and capacity constraints. However, to keep the model simple, I do not allow rigs to explicitly condition value functions, prices, or relocation decisions, on a backlog 'state'. In other words, for parsimony, I model the value of matching in a location as if matching is 'on-demand', but using long-run average matching probabilities and prices.

Here τ is the length of a contract in months, $V_{l,y}$ is the ex-ante value of available capital, $U_{l,y}$ is the value of unemployed capital, $\mathbb{P}_{exit}$ is an exit shock for unmatched potential wells. So, $1 - \mathbb{P}_{exit}$ is the probability that the unmatched potential well does not exit and continues to search if the match is rejected. However, note that this occurs off the equilibrium path since all matches are accepted.

The value $\beta(1-\mathbb{P}_{exit})W_{l,x,y}$ is the well's outside option (which, again, occurs off the equilibrium path since all matches are accepted and wells either find a match or choose to immediately exit). For simplicity I assume that if a well rejects a match then it will target the same type of capital and so W is subscripted by the type of capital y as well as the location l. The value $W_{l,x,y}$ is given as:

$$W_{l,x,y} = q_{l,y}^{project} \sum_{s=0}^{\tau-1} \beta^s (m(x,y) - p_l(x,y)) \tag{10}$$

which is the probability that the capital type is not at its capacity constraint, multiplied by the payoff to the well of matching. Note that if the capital is at its capacity constraint (which happens with probability $1 - q_{l,y}^{project}$) then the well exits immediately since the backlog is too long, receiving a payoff of 0, and so this term disappears.

4.5 Equilibrium

Definition 1. *Equilibrium is a set of prices $p_l(x,y)$, matching probabilities $q_{l,y}^{project}$ and $q_{l,y}^{capital}$, and a spatial capital distribution $\{n_{l,y}\}_{l \in L, y \in \{low,mid,high\}}$ that satisfies:*

1. *Supply Side Equilibrium Optimal location decision by rigs subject to the equilibrium average prices $\bar{p}_{l,y}$ in each location and the equilibrium probability of matching $q_{l,y}^{capital}$ in each location, resulting in a spatial distribution of capital satisfying Equations (4) - (6).*

2. *Demand Side Equilibrium Optimal targeting decision by potential projects - given equilibrium prices and the equilibrium total number of rigs $n_{l,y}$ in each location - that satisfies Equations (1) - (3).*

3. *Prices $p_l(x,y)$ determined by Nash bargaining.*

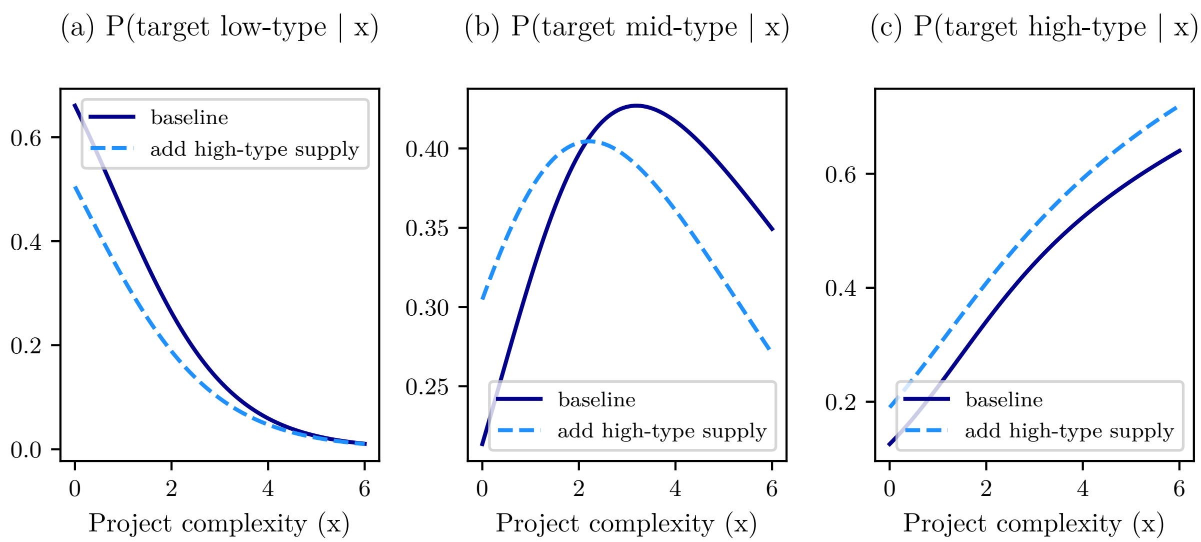
4. *Expectations of agents consistent with the long-run equilibrium.*

4.5.1 The within-location equilibrium with two-sided heterogeneity

A key difference between the model in this paper and past work which studies markets where agents are relatively homogeneous (such as bulk shipping in Brancaccio et al. (2020)) is that I allow for two-sided vertical heterogeneity. Although this feature is important to understanding capital relocation in the offshore oil and gas industry, it adds substantial complexity to the equilibrium. In particular - with two-sided heterogeneity in the model - the entry of different types of rigs within a location will change relative prices and relative capacity constraints. As a result, potential projects may change their targeting behavior, thereby causing a reallocation of matches. This within-location equilibrium then affects capital location choices since it determines equilibrium prices and utilization. To highlight intuitively how two-sided heterogeneity shapes the within-location equilibrium I perform a comparative statics exercise in Figure 4.

Figure 4 shows the probability that each type of potential project (on the x-axis) targets a particular type of capital within a location. In the baseline (shown by the solid dark-blue line) simple projects tend to target low-type capital, average complexity projects target mid-type capital, and complex projects target high-type capital. Next I consider the effects after an increase in high-type capital, shown by the dashed light-blue line. Initially, the entry of high-type capital relaxes the high-type capacity constraints and lowers high-type prices. This causes projects to redirect their targeting towards high-type capital and away from mid-type and low-type capital, resulting in an upwards shift of the dashed light-blue line. This then relaxes the mid-type capacity constraint and lowers the mid-type price, which causes a further equilibrium shift in project targeting behavior away from low-type capital and towards mid-type capital. Notably, simple projects are *more likely* to target mid-type capital after high-type entry. Overall, the entry of high-type capital reduces prices and relaxes capacity constraints for all capital types, and causes all types of capital to be reallocated towards relatively simpler types of projects.

Figure 4: Within-location equilibrium: effects of high-type capital entry



Notes: This figure is a comparative statics exercise that shows the effect of a increase in high-type capital on the equilibrium targeting behavior of potential projects within a location. Recall that each potential project chooses - given prices and capacity constraints - which type of capital to target using a logit model. This figure illustrates this targeting behavior: conditional on an project complexity type (x) on the x-axis, the y-axis shows the probability that it targets a particular type of capital. (So, for each x, these graphs can be summed vertically so that $1 = P(\text{target low-type }|\text{x}) + P(\text{target mid-type }|\text{x}) + P(\text{target high-type }|\text{x})$.) The main point this figure highlights (discussed further in the text) is that high-type capital entry affects the targeting behavior of potential projects by changing equilibrium prices and relaxing capacity constraints. In equilibrium this reallocates matches from existing mid and low-type capital to high-type capital, and also affects sorting behavior within the location.

5 Estimating the model

5.1 Overview

I provide an overview of the parametric assumptions used, and how the parameters are estimated or calibrated, in Table 3. I perform the estimation in two steps (after calibrating certain parameters detailed in Table 3):

1. Use conditional choice probabilities/maximum likelihood to recover the costs/benefits of moving location $\mathbf{c} = \left(\{c_{l,y}\}_{l\in L, y\in\{low,mid,high\}}, \sigma_\epsilon, b_{stay}\right)$.
2. Estimate the parameters which underlie match value function $m(x, y)$ and demand $\{\lambda_l, \mu_l, \sigma_l^2\}_{l\in L}$ using the simulated method of moments.

Before getting into the detail of the estimation, I first justify the calibration values and discuss the parametric assumptions.

Justification for the calibrated values The discount factor is not identified, as is typically the case in dynamic discrete choice models: Magnac and Thesmar (2002). So, I set the monthly discount factor $\beta = 0.99$. I calibrate the contract length $\tau = 6$ which is approximately the mean contract length in the data. I calibrate the maximum backlog to $t_{backlog} = 5$ months, which is around the 75 percentile of backlog in the deepwater US Gulf of Mexico.[24]

I also calibrate the moving cost parameter c_d. Long-range capital movements are usually accomplished by a 'dry tow', which means that the capital is loaded onto a ship and moved to the new location. The speed of a dry tow is typically 14 knots (16.11 miles per hour) (Golson (2014)). Since rigs are moved by the similar tow boats, and the cost of towing is proportional to the distance, I convert the distance between fields by the tow speed and calibrate the per-day cost of towing as $c_d = \$0.25$ million.[25]

[24]In my dataset the US market is the only market where backlog data are systematically available.

[25]I choose this value based on the assumed dayrate for a heavy lift marine transport ship undertaking a 'wet tow' suggested by industry practitioners in Terpstra et al. (2013). While a 'dry tow' may be more expensive than a 'wet tow' since it is faster, industry practitioners suggest that there are also substantial other cost savings to using a dry tow (Dockwise (2012)) and so I assume that overall these values are comparable.

Table 3: Overview of how the parameters are computed

Object	**Notation**	**Parameterization**	**Param.**	**Method**
Discount rate, monthly	β			Calibrated: 0.99
Contract length, months	τ			Calibrated: 6
Max. backlog, months	$t_{backlog}$			Calibrated: 5
Bargaining weight	δ			Calibrated: 0.5
Well exit rate	$\mathbb{P}_{exit}$			Calibrated: 0.5
Relocation cost	c_d	Total cost $= c_d \cdot d_{l,l'}$	c_d	Calibrated: 0.25
Costs	$c_{l,y}$	Markup: $c_{l,y} = \gamma_l \bar{p}_{l,y}$	γ_l	Estimate step 1
Remain in loc.	b_{stay}		b_{stay}	Estimate step 1
Preference shock	σ_ϵ	Extreme value/std. dev	σ_ϵ	Estimate step 1
Demand distribution	$f_l^{entry}(x)$	Folded normal/mean	μ_l	Estimate step 2
Demand distribution	$f_l^{entry}(x)$	Folded normal/std. dev	σ_l	Estimate step 2
Demand draws	D_l	Poission dist/mean	λ_l	Estimate step 2
Match value	$m(x, y)$	$m_{0,y} + m_{1,y}x$	$m_{0,y}$	Estimate step 2
Match value	$m(x, y)$	$m_{0,y} + m_{1,y}x$	$m_{1,y}$	Estimate step 2

Note: This table provides an overview of the parametric assumptions used and how the parameters are estimated or calibrated.

I need to calibrate the bargaining parameter and in this draft I assume that the parties split the match surplus equally and set this to $\delta = 0.5$.[26]. In addition I need to calibrate the exogenous exit rate in the well's outside option. This is difficult because by assumption all matches are accepted and so 'taking the outside option' occurs off the equilibrium path. For this draft, I choose a value of $\mathbb{P}_{exit} = 0.5$.[27]

Discussion of parametric assumptions I assume that the distribution of complexity for new wells is given by a folded normal:

$$f_l^{entry}(x) = \frac{1}{\sigma_l} \frac{\phi(\frac{x-\mu_l}{\sigma_l})}{1 - \Phi(\frac{-\mu_l}{\sigma_l})} \tag{11}$$

where $\phi(.)$ denotes the standard normal PDF and $\Phi(.)$ denotes the standard normal CDF.

Estimating a separate cost for each capital type in each location would require estimating 18 different costs. However, given there are several 'thin' markets where the number of relocations for a given capital type are small, I choose to parametrize costs in the following way:

$$c_{l,y} = \gamma_l \bar{p}_{l,y} \tag{12}$$

Here $\gamma_l \in [0, 1]$ is a location-specific scale parameter that relates costs to the average price in each location. Note that $1 - \gamma_l$ is the capital's markup in location l and so a low γ_l corresponds to a high markup and a high γ_l corresponds to a low markup. In summary, there are ten cost parameters that need to be estimated (eight scale parameters, the stay-put benefit, and the standard deviation of the preference shocks σ_ϵ).

I assume that the match value is given by the functional form $m(x, y) = m_{0,y} + m_{1,y}x$ where $m_{0,y}$ and $m_{1,y}$ are parameters that depend on the type of rig y. Importantly, the parameter $m_{1,y}$ indexes the complementaries between applying a type-y rig to a type-x well. I further discuss these complementaries in the estimation results (Section 6).

I now discuss the two estimation steps in more detail.

[26] This is somewhat close to the value in Vreugdenhil (2020) for the shallow water market where $\delta = 0.4$.

[27] Brancaccio et al. (2020) also need to calibrate a similar value for their 'exporter survival rate'.

Step 1: Computing parameters that determine the costs/benefits of moving

I use the observed choice probabilities of moving between locations to compute **c**. This section is similar to the estimation strategy in Brancaccio et al. (2020). The location-specific drilling costs **c** are identified from differences in the value of moving that cannot be explained by distance alone (or by differences in capital prices). The benefit of remaining in location b_{stay} is pinned down by the persistence of rigs remaining unemployed in a location beyond what estimated costs (and observed prices and match probabilities) would predict alone. The scale parameter σ_ϵ is pinned down by the scale of observed prices.

I estimate the parameters in this section using maximum likelihood. I provide more information about how I compute the value functions and the exact algorithm for estimation in Appendix C.1.

I note that I assume that drilling costs were relatively unaffected in the immediate term after the 2010 deepwater horizon incident and so do not allow costs to change before and after 2010. In principle it would be possible to relax this assumption by allowing for different costs before and after May 2010. However, given data limitations, and the fact that changes to US regulations shortly after 2010 were estimated to have relatively small costs on the industry e.g. BOEMRE (2010) (as opposed to the 2016 changes which I study in the counterfactuals which generated much more heated debate), I opt to keep these costs the same.

Step 2: Computing the match value and demand

A key challenge is that, although I observe contracts (price, duration, and the parties) in each location, I only have matched contract-project data where I see the exact well type drilled in the US market. For non-US markets, I therefore employ a strategy of estimating demand from the price/contract data alone (recall that 'demand' is the underlying distribution of wells). Intuitively, this strategy requires knowing the mapping between prices and well types so the distribution of prices can be inverted to recover the underlying distribution of well types. Therefore, I spilt Step 2 into two sub-steps: I first retrieve the parameters that underlie the match value function (as well as demand) in the US market. Then, I use the estimated match value parameters to invert the distribution of prices to retrieve the equilibrium distribution of potential projects.

Moments I use the following moments in the simulated method of moments estimation procedure:

- *(All markets)* The average price of each type of capital (3 moments)
- *(All markets)* The average capital utilization (1 moment)
- *(US market only)* The average well complexity match for each type of capital (3 moments)
- *(US market only)* An auxiliary price regression (more detail below) (5 moments)

I include moments from the following auxiliary regression of prices on project complexity and capital type for each contract where project characteristics are observed:

$$\text{price}_i = \beta_{0,y} + \beta_1 \text{complexity}_i + \beta_2 \cdot (\text{max drilling depth})_i \cdot \text{complexity}_i + \epsilon_i \tag{13}$$

where $\beta_{y,0}$ is a capital-specific fixed effect. This auxiliary price regression results in 5 additional moments to fit (i.e. the coefficients $\{\beta_{0,y}\}_{y\in\{low,mid,high\}}, \beta_1, \beta_2$).

Computation I provide information about how I compute the demand-side equilibrium in Appendix C.2. Using this algorithm, I first compute the equilibrium in the US which returns demand in the US market and the match-value function. Using this match-value function, I next estimate demand in each remaining location. To fit the parameters I use the standard GMM criterion function: denoting the empirical moments g_d and the simulated moments g_s generated by a particular set of the parameters, I fit the simulated moments to the empirical moments g_d by minimizing:

$$(g_d - g_s)'\Omega(g_d - g_s) \tag{14}$$

and for this draft I set Ω as the identity matrix, except for the price and utilization moments which I weight by 100 to ensure they are of the same scale as the other moments.

Identification The match value parameters $\boldsymbol{m}$ are determined by two sets of moments. First, the auxiliary regression in Equation 13 captures the direct relationship between prices and contract characteristics through the match value in the Nash Bargaining solution. Second, the moments for the average project complexity matched with each type of capital provide information about the positive sorting patterns in the industry (specifically, these moments are increasing in capital type so that more complex wells are matched with more efficient capital). The model rationalizes these sorting patterns through the search technology which allows each project to target capital that it is best matched to. To put it succinctly, the empirical sorting patterns in the data provide information on the value of the match between capital and projects.

Once the match value parameters are pinned down, the parameters that characterize the distribution of project entry (μ_l, σ_l) are determined by moments related to the distribution of prices and observed matches. Finally, the poisson parameter for new project entry λ_l is determined by the average utilization.

6 Results

Step 1: Computing parameters that determine the costs/benefits of moving

The results for the costs are in Table 4. Differences in costs can arise due to differences in geological or weather conditions, differences in labor costs, and regulation. Overall the estimates reveal heterogeneity in drilling costs across regions, and highlight that both regulation and geological differences may drive costs. For example, Europe has some of the highest drilling costs globally and is known to have stringent offshore regulatory regimes; indeed, the 'North Sea standards' in Europe are often viewed within the industry as best-practice in reducing spills and other incidents (but with the tradeoff of higher drilling costs). Costs may also be high due to geological factors: the Central Americas has high drilling costs but these are unlikely to occur due to the stringency of regulation. The US has notably some of the lowest drilling costs globally which stems from two factors. First, the regulatory regime in the US more relaxed than many other rich countries (for example, those countries operating in the North Sea). Second, the proximity to the world-class well-services industry in Texas and Louisiana coupled with the fact that the deepwater of the Gulf of Mexico has been explored for many decades (which may lead to fewer unexpected drilling problems), may lower costs.

Since average prices increase with rig type, the constant markup assumption in each location returns costs that also increase with rig type. High-specification rigs have around 1.5-2 the drilling cost of a low-specification rigs.

Table 4: Supply-side estimation results

	Drilling cost ($c_{l,y} = \gamma \bar{p}_{l,y}$)			
	Scale parameter	Low-type	Mid-type	High-type
	γ_l	$c_{l,low}$	$c_{l,mid}$	$c_{l,high}$
Africa	0.86	0.26	0.3	0.42
	(0.804, 0.908)	(0.245, 0.277)	(0.28, 0.316)	(0.394, 0.445)
Asia	0.9	0.2	0.29	0.43
	(0.826, 0.952)	(0.186, 0.214)	(0.27, 0.312)	(0.4, 0.461)
Australia	0.88	0.24	0.29	0.45
	(0.832, 0.923)	(0.228, 0.253)	(0.272, 0.302)	(0.419, 0.464)
Central Am.	0.94	0.21	0.42	0.5
	(0.892, 0.974)	(0.202, 0.22)	(0.4, 0.437)	(0.472, 0.516)
Europe	0.88	0.28	0.35	0.45
	(0.821, 0.914)	(0.261, 0.29)	(0.328, 0.365)	(0.418, 0.465)
Mid. East	0.89	0.19	0.34	0.4
	(0.838, 0.93)	(0.176, 0.195)	(0.321, 0.356)	(0.375, 0.416)
South Am.	0.86	0.21	0.24	0.4
	(0.795, 0.899)	(0.191, 0.216)	(0.221, 0.25)	(0.371, 0.42)
US	0.84	0.2	0.28	0.36
	(0.777, 0.889)	(0.184, 0.211)	(0.256, 0.293)	(0.33, 0.378)
Preference Shock	0.1			
	(0.087, 0.126)			
Stay Put Benefit	0.11			
	(0.073, 0.157)			
Relocation Cost	0.25			
	(n.a.)			

Note: Bootstrapped 95% confidence intervals in brackets using 200 replications. Values in millions of US dollars/day. Relocation costs are calibrated as the daily costs (and distances are converted in the estimation from miles to days of travel at 16.11 miles/hour). To estimate the drilling costs, I assume that they are in the form of a markup over the average location-capital-specific average price. Therefore, eight scale parameters γ_l are estimated, and the interpretation is that $1 - \gamma_l$ is a markup. I present the γ_l parameters and the implied costs in the table.

Table 5: Demand-side estimation results

(a) Demand Parameters

Location	Coefficients		
	# Entry	Mean	Std. Dev
	λ_l	μ_l	σ_l
Africa	6.1	1.1	2.8
	(6.071, 6.123)	(1.089, 1.143)	(2.794, 2.801)
Asia	3.96	1.53	2.27
	(3.888, 3.992)	(1.439, 1.632)	(2.055, 2.28)
Australia	3.53	1.2	2.25
	(3.514, 3.558)	(1.107, 1.273)	(2.018, 2.282)
Central Am.	2.0	1.34	2.2
	(1.997, 2.042)	(1.194, 1.537)	(1.933, 2.273)
Europe	8.04	0.6	1.4
	(8.008, 8.128)	(0.572, 0.651)	(1.356, 1.487)
Mid East	2.04	0.51	1.98
	(2.015, 2.075)	(0.4, 1.045)	(1.878, 2.775)
South Am.	7.69	0.91	2.25
	(7.499, 7.826)	(0.909, 1.371)	(2.17, 2.719)
US	8.78	2.0	1.59
	(8.674, 8.845)	(1.865, 2.098)	(1.513, 1.664)

(b) Matching Parameters

Type	Coefficients	
	Match Value	
	$m_{0,y}$	$m_{1,y}$
Low	0.95	-0.42
	(0.868, 0.998)	(-0.481, -0.398)
Mid	0.85	-0.12
	(0.823, 0.928)	(-0.144, -0.098)
High	0.48	0.06
	(0.45, 0.525)	(0.044, 0.075)

Note: Confidence intervals at 95% using 200 bootstrap replications in brackets. Panel (a) shows the estimated demand parameters which are computed using Simulated Method of Moments. Panel (b) shows the estimated match value parameters which are in the form $m(x, y) = m_{0,y} + m_{1,y}x$. As discussed in the text, these parameters should satisfy increasing differences but the sign and ordering of the parameters is theoretically ambiguous.

Step 2: Computing the match value and demand

The fit of the model is detailed in Table 8; the model appears to closely fit the sample moments. Turning first to the demand results in Table 5, the estimates reveal substantial differences in demand across the world. For example, the mean project complexity terms μ_l are consistent with the utilization of different types of capital in different fields. For instance, Europe is a primary markets for low-specification rigs, and contains simpler projects. By contrast, the US is a primary market for high-specification rigs and contains complex projects that involve drilling deep and high-pressure wells.

Next, consider the match value results for $\boldsymbol{m}$ in Table 5. Theoretically, these estimates must satisfy increasing differences to generate the empirical positive sorting patterns between capital efficiency and project complexity. The empirical estimates satisfy this increasing differences requirement. Beyond increasing differences, however, the exact sign and ordering of the coefficients in theoretically ambiguous since the match value represents both costs and benefits of drilling different well complexities. For example, for the match value slope parameter $m_{1,y}$, this may be negative for some rig types (e.g. complex projects incur more costs to the well owners - such as drilling delays or the need to replace a damaged part of the well - and this may differ with rig type), or they may be positive (more complex projects tend to produce more oil). Overall, the match value estimates indicate that low-specification rigs have both a competitive advantage and a comparative advantage in drilling simple projects. Conversely, high-specification rigs have an advantage in drilling more complex wells.

7 Counterfactuals

7.1 Summary

I investigate three counterfactual scenarios to study the role of incomplete regulation in the global market for deepwater drilling rigs. These counterfactuals are 1. an increase drilling standards only in the US market 2. an increase in drilling standards in a coalition of 'rich countries' 3. a worldwide agreement on increasing drilling standards.

Quantifying oil spilled For each counterfactual I quantify the (expected) volume of oil spilled in each location. To do this I closely follow the engineering model used by the regulator to assess counterfactual policies in the US market (e.g. in BOEM (2016)) and I detail this model in the Appendix. Broadly, I map well complexity of an individual project into a production volume and then use the engineering model to map it into an (expected) volume of oil spilled. Then, given the equilibrium number and types of matches predicted by the model in each location, the model can predicts both expected profits and an expected volume of oil spilled.

In order to evaluate the counterfactuals I need a measure of global social welfare. To compute this I need a value for the social cost of an oil spill to map the model-predicted volume of oil spilled into a dollar figure, which can be weighed against the model-predicted change in profits. In the main analysis I value the costs of a barrel of oil spilled at \$3700 in all locations (this is the value that was used to compute the original regulatory impact analysis of the regulations in BSEE (2016)). I make this assumption because of sparse data about the social cost of oil spills across different regions worldwide. However, I check robustness by showing that for wide range of alternative assumptions about heterogeneous social costs leakage remains a concern using a bounding exercise in Table 7b.

Quantifying leakage For each scenario I compute 'leakage' statistics in addition to social welfare and other metrics. Leakage is defined as the change in a particular metric in other regions for a 1 unit change in the newly regulated area. So, for example, a leakage number of 0.5 for profits would imply that for every \$1 in profit lost due to the regulation in the US, \$0.5 more in profit is generated elsewhere in the world through capital relocation. Similarly, a leakage number of 0.5 for the volume of oil spilled means that for every barrel of oil saved in the US market, 0.5 more barrels are spilled elsewhere.

Background on the policy The policy to increase drilling standards is motivated by recent regulations in the US (for example, see the Federal Register (2016)) which attempt to increase environmental standards to be closer to European standards ('North Sea' standards).

To run the counterfactuals I need to take a stand on the cost increase and oil spill risk reduction of the standards. The policy experiment I investigate is a 20% increase in the cost of deepwater drilling in the US for each rig type, which is based on an industry-commissioned study into the effects of rules that models a scenario of an increase in costs of around $99 million per well (the study is Quest Offshore (2015) and the per-well conversion is from Mason (2019)).[28] Specifically, I implement the cost as a 20% increase in the per-period cost of drilling $c_{l,y}$ for each rig type using the US values (so the costs in other markets increase additively by the same increase in costs as the US market).

In practice, increasing drilling standards involves a suite of regulations and some of these regulations are designed to improve the blowout preventer technology used on-board the rigs. Therefore, a natural question is whether the regulation should be alternatively modeled as a once-off investment cost rather than an increase in the per-period drilling cost $c_{l,y}$. I opt to model it as an increase in per-period drilling costs because that is what other studies of the regulation do (e.g. Quest Offshore (2015) and BSEE (2016)). These other studies suggest most of the costs of increasing drilling standards come from ongoing increased compliance costs.

I assume a spill risk reduction of 20% from introducing these standards. Although this is at the high end of a range of risk reductions suggested by the regulator's sensitivity analysis of the rule, this range has been criticized as being too conservative Krupnick and Echarte (2018). An additional reason for choosing the 20% value is this is also one of the scenarios considered by external experts in Krupnick and Echarte (2018).[29] Since there is some uncertainty about the true cost and the true risk reduction, I also perform numerous robustness tests for different assumptions in Table 7a.

Since the increase in standards came into force in the US in 2016, one might ask whether the effects of these standards could be directly tested in the data, rather than using the framework. Two factors make a direct test of the regulation infeasible. First, I only have access to data up to 2016 and so I only observe the market before the regulations were implemented. Second, even if more recent data were available, shortly after the new rules came into effect the Trump administration took office. The Interior Department under the new administration reportedly

[28] In other words, for the distribution of matches in the baseline scenario in the US market, a 20% increase in drilling costs corresponds to approximately a $99 million per well average cost increase.

[29] It is worth mentioning that both the risk reduction and cost increase are higher than the values considered by the BSEE in their original regulatory impact statement BSEE (2016) who, for instance, choose a 'conservative' value of only 1 percent risk reduction in their main analysis. Again, I opt to not use these lower numbers because they were criticised at being too conservative (in terms of the risk reduction in Krupnick and Echarte (2018) and the costs in Quest Offshore (2015)).

undercut the rules, handing out an unprecedented number of waivers to the new standards, and led some lobby groups to ask: "Are these rules becoming meaningless under the Trump administration?".[30] Therefore, although these new rules were formally on the books in 2016, it is not clear whether they were binding on the industry for a meaningful period of time.

Diagnosing ineffective vs effective regulation More stringent regulation tends to decrease industry profits and also oil spilled. Therefore, the regulation will increase global welfare if the value of the reduction in oil spilled outweighs the reduction in industry profits.

As the counterfactuals move from unilateral regulation to more complete regulation, two forces work to increase welfare. First, the total number of regions under regulation increases and so absolute welfare may increase mechanically. Second, since regulation is more complete there is less leakage. To differentiate between these two forces, I also compute a benchmark 'no relocations' world, which captures the welfare change if the regulation was introduced without leakage.[31] Therefore, I refer to leakage as making the regulation less effective if the total welfare change is far from the 'no relocation' benchmark.

One might ask which elements of the model are most important to producing high levels of relocation. A key factor is that markets outside the US are somewhat constrained on the supply side, implying there is enough excess demand (i.e. unmatched projects) to soak up rig entry.

7.2 Results

A summary of all the counterfactuals in given in Table 6. I now describe the results of each counterfactual.

[30] For example, see https://www.politico.com/story/2019/02/25/offshore-drilling-trump-administration-interior-department-1190762 which details the waivers and the effect on the industry.

[31] This benchmark also captures that different locations vary in terms of their distributions of demand $f_l^{entry}(x)$ and different drilling costs $c_{l,y}$. These primitives may affect welfare, even without any capital relocation: for instance, if one market tends to contain wells with low profit margins but high social costs, the regulation may be particularly successful in improving welfare.

Table 6: Counterfactuals

Counterfactual	Leakage (Per unit)	US change	Total changes Decomp. by mkts with... Δ reg.	No Δ reg.	Global
US-only ↑ standards					
(Expected) Oil Spilled	0.48	-41.7	-11.5	5.6	-6.0
Profits	0.45	-53.1	-11.6	5.2	-6.4
Welfare			10.9	-7.7	3.2
(Welfare: No Relocations)			*(11.8)*	*(0)*	*(11.8)*
Coalition ↑ standards					
(Expected) Oil Spilled	0.37	-33.8	-18.1	6.8	-11.4
Profits	0.33	-42.7	-18.5	6.1	-12.4
Welfare			15.5	-11.2	4.3
(Welfare: No Relocations)			*(18.3)*	*(0)*	*(18.3)*
Global ↑ standards					
(Expected) Oil Spilled	0.04	-23.0	-21.8	0.9	-21.0
Profits	0.09	-27.6	-22.3	2.0	-20.3
Welfare			18.7	6.6	25.3
(Welfare: No Relocations)			*(28.2)*	*(0)*	*(28.2)*

Note: This table contains the results of the counterfactuals compared to the model baseline. The numbers (except for the leakage statistics) are all given in terms of percent changes. So, for example, a number of -41.7 corresponds to a 41.7% decrease. Leakage per unit is defined as the change in other markets for a 1 unit change in the regulated markets. US-only standards is a 20% cost increase with a 20% expected oil spill risk decrease in the US market. The coalition counterfactual applies these new standards to the US, Australia, and South America. The global regulation counterfactual applies these standards uniformly to all regions in the world. In the baseline, Europe has the new drilling standards (these are called 'North Sea standards') but all other regions do not.

7.2.1 Baseline

In the baseline I assume there are two regimes: the European market which has the more stringent North Sea standards, and the rest of the world, which does not. One may ask whether countries in Africa and Asia may have lower standards than in the United States. However, drilling companies like Transocean and oil well owners like BP and Chevron are multinational companies whose internal standards may provide a lower bound on drilling standards worldwide, even if the institutions in a particular country do not stringently regulate drilling. In addition, this assumption is conservative when considering that the main results in this section suggest that incomplete regulation is relatively ineffective. Specifically, if this assumption was violated and poorer regions do indeed have lower drilling standards, this would exacerbate leakage of pollution from the US-only and the coalition of rich countries counterfactuals considered in this paper, further undermining the effectiveness of piecemeal regulation.

7.2.2 US-only regulation

I first consider the effect of an increase in drilling standards only in the US market.

The results in Table 6 show that the regulations reduce oil spilled in the US by 41.7% but also reduce profits by 53.1%. If a policymaker looked at the effects of the regulation on the US market in isolation (as is typically the case when doing cost/benefit analyses in this industry for the offshore oil and gas leasing program and other regulation e.g. BOEM (2016)) they might conclude that the regulation is effective in reducing oil spills, albeit expensive, leading to an increase in social welfare of 10.9%. However, looking at the full results on the global oil and gas industry using the framework in this paper suggests the regulation is less effective, only increasing welfare by 3.1%. The results show that incomplete regulation substantially undercuts the policy: for every barrel of oil not spilled in the US due to higher standards, 0.48 barrels are spilled elsewhere. Similarly, for every $1 in profit lost in the US, $0.45 is generated elsewhere. The less than 1:1 ratio in profit shifting is in part due to mismatch: rigs move to regions where they are less likely to match or where the composition of demand (i.e. the types of wells that need to be drilled) are a bad match for the rig specification; I discuss misallocation further in the next section.

Finally, if the regulation was just applied to the US market and rig locations were fixed (the 'no relocations' benchmark row), the regulation would be almost four times effective and increase global social welfare by 11.8% compared to only 3.1% with relocations. This suggests that accounting for leakage is key to quantifying the efficacy of the regulation and that more coordinated changes in regulation might be more effective at improving social welfare, and I discuss this in the next section.

7.2.3 Coalition which increases standards

I consider a more coordinated increase in standards through a coalition of 'richer countries' (incorporating the US, Australia, and South America) that increases their collective environmental stringency to North Sea standards. These parties to a regional agreement align approximately with what is known as the 'regulated areas' of the global oil and gas industry (see e.g. Holand (2017) who uses this terminology): regions which collect oil and gas incident data with mandatory reporting laws.

The leakage per unit figures in Table 6 are lower for coordinated regulation than for US-only regulation (by approximately one quarter). As a consequence, the decrease in profit due to the regulations in the US is lower (but so is the decrease in expected oil spilled). Overall, the global reduction in expected oil spilled, and also profits, is higher than for US-only regulation. This result occurs both due to wider adoption of costly regulation (so profits are mechanically lower in more regions) and also less misallocation from less leakage. The total effect is to reduce global social welfare in the offshore oil and gas industry by 4.3%. Similar to the US-only regulation counterfactual, this total effect is relatively ineffective when compared to the regulation implemented without capital relocations, which would lead to a much larger 18.3% increase in social welfare.

The results indicate that a coalition of rich countries would be relatively unsuccessful in improving social welfare solely based on the efficiency of the policy. In addition, there are equity reasons why this particular coalition may be a less desirable policy: by only regulating richer regions, leakage causes pollution and profits flow to the poorer regions of Africa, Asia, the Middle East, and the Central Americas. Since these regions only have the weaker regulation, the model predicts that the leakage of pollution outweighs the leakage of profits and overall results in a net decrease in social welfare in these regions of 11.2% of social welfare. Hence, this policy tends to create a 'pollution haven' in poorer countries.

7.2.4 Global regulation

Finally, I consider how a coordinated global agreement on drilling standards would affect the marketplace. Since regulation is now uniform, there are no unregulated areas. There is a small amount of leakage from the areas with a change in regulation to Europe, which already has the high standards.[32] Since Europe is already a regulated market, leakage of drilling activity into Europe actually leads to a net *increase* in social welfare in the European market leading to an increase in welfare of 6.6%. Globally, the decrease in profits and expected oil spilled is greater than under US-only regulation or the coalition counterfactual. Again, the difference in terms of profits is due both to mechanical effects - more areas under regulation imply less profits worldwide - and misallocation. Overall, the regulation improves global welfare by 25.3%.

As might be expected, a global agreement covers more regions and so the total increase in welfare is higher than in the coalition or unilateral regulation counterfactuals. However, the reduction in leakage is also a key reason for the difference between the counterfactuals. For example, leakage in the unilateral regulation scenario undercuts the welfare increase by almost two-thirds compared to the case with no capital relocation, from 11.8% to 3.2%. By comparison, the overall effect of global regulation is quite similar to the benchmark effect on social welfare without capital relocation (which is 28.2%).

7.3 Decompositions and alternative assumptions

7.3.1 Role of two-sided vertical heterogeneity

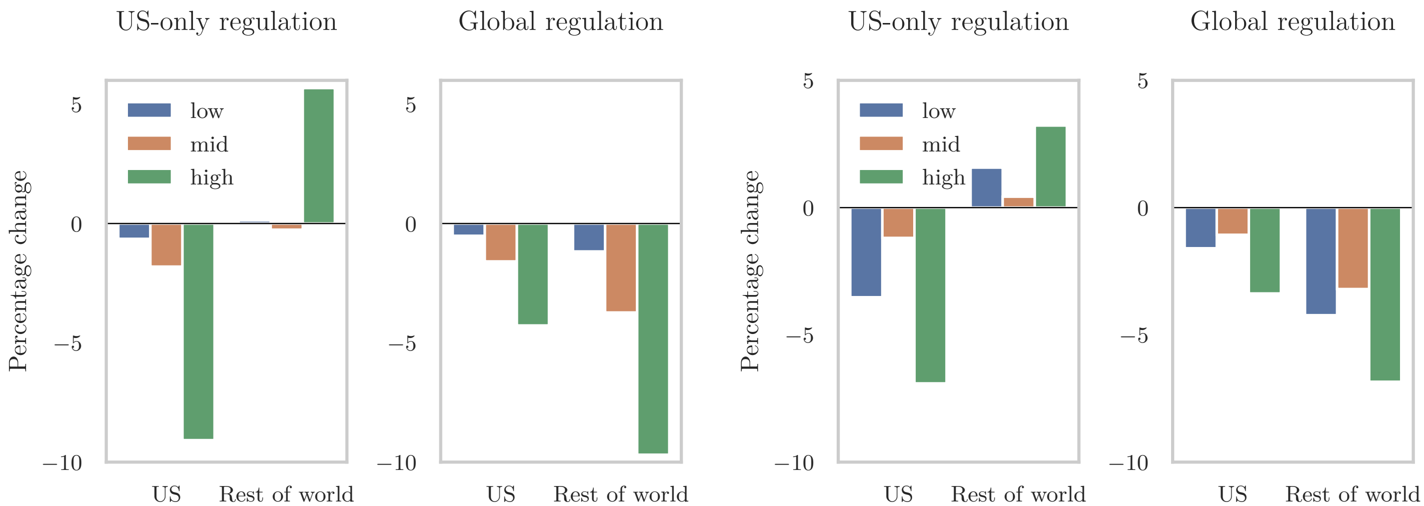
A key difference between this paper and previous work is the framework and empirical application feature two-sided vertical heterogeneity. Quantitatively, how much does this new feature affect the results compared to a simpler model without two-sided heterogeneity? To answer this question I first decompose the total (expected) spill and total profits by rig type in Figure 5(a) and (b). Then, I shut down two-sided heterogeneity and compute results for the case where all rigs are mid-specification rigs in Figure 5(c).

[32] Recall that I define leakage as the change in profits or (expected) oil spilled from newly regulated areas to the rest of the world.

Figure 5: Role of two-sided vertical heterogeneity

(b) Decomposition: total (expected) spill

(c) Decomposition: total profit



(a) Model without two-sided vertical heterogeneity

Counterfactual	**Leakage**		**Welfare**
	(Exp.) Oil Spilled	Profits	Global
US-only ↑ standards	0.3	0.23	13.1
(Full Model)	*0.48*	*0.45*	*3.2*
Coalition ↑ standards	0.16	0.13	21.4
(Full Model)	*0.37*	*0.33*	*4.3*
Global ↑ standards	0.02	0.09	43.4
(Full Model)	*0.04*	*0.09*	*25.3*

Note: Table (a): Decomposition of the total change in total (expected) oil spilled by rig type. Table (b): Decomposition of the total change in total profit by rig type. For both (a) and (b), US-only regulation tends to reduce profits and (expected) oil spilled in the US market but increases profits and spills in the rest of the world through rig relocation. Global regulation tends to reduce profits and (expected) spills everywhere. Table (c): This shows the results from the full model and a world without two-sided vertical heterogeneity (i.e. where low and high specification rigs are replaced with medium specification rigs).

Figure 5(a) and (b) show that high-specification rigs are responsible for a greater share of changes in profit and (expected) oil spilled than other rig types. This occurs for two reasons. First, within a location, different rigs sort to different wells: for example, high-specification rigs tend to drill complex projects which tend to have higher (expected) oil spill numbers. Hence, a 20% decrease in oil spilled for these complex projects is associated with a greater aggregate oil spill reduction for high-specification rigs. Second, high-specification rigs tend to move much more frequently than other rig types both in the model and in the data, as documented in Section 3. Therefore, after a change in regulation, high-specification rigs tend to relocate disproportionally compared to other types. This relocation effect is particularly noticeable in the change in the 'rest of world' after US-only regulation.

Figure 5(a) and (b) also capture some other interesting behavior. For example, the change in profits for mid-specification rigs in Figure 5 is less than low-specification rigs. One reason this occurs is because, in equilibrium, high-specification rig exit (and a greater increase in $c_{l,y}$ compared to other types) causes an increase in the probability of a mid-specification rig match through changes in well targeting behavior, which undercuts the reduction in mid-specification profits and also dampens incentives to relocate.

The results in Figure 5(c) show that failing to account for two-sided vertical heterogeneity substantially affects the conclusions of the paper. The overall effects of the counterfactuals are much larger without two-sided heterogeneity. For instance, a US-only increase in standards would increase social welfare by 13.1% versus 3.2% in the main model, and a global increase in standards would increase social welfare by 43.4% versus 25.3% in the main model. A key reason behind this is that, without two-sided vertical heterogeneity, the model predicts much less leakage. For example, for the US-only increase in standards, in the full model leakage of (expected) oil spilled is 0.48 barrels for every barrel not spilled in the US market; without two-sided heterogeneity this falls to 0.3 barrels. Similarly, the leakage of profits is \$0.45 for every \$1 change in the full model; without two-sided heterogeneity this falls to \$0.23.

The intuition behind these differences is as follows. As previously mentioned, high-specification rigs tend to move much more frequently than other specification rigs. Therefore, the relocation of high-specification rigs to a location without the regulation tends to disproportionally relax supply constraints on complex wells. Although these complex wells are highly profitable, the social welfare of these wells tends to be negative without the new regulation. Hence, the relocation of high-specification rigs tends to result in the relocation of socially costly wells, substantially undercutting the local regulation.[33] A model with only 'average' mid-specification rigs does not capture this behavior, since a relocation of these 'average' rigs tends to result in more 'average' complexity wells being drilled in other locations. So, this simpler model underestimates leakage and overstates the benefits of the regulation. Amplifying these effects is that the US market (which is subject to new regulation in all the counterfactuals) also tends to contain relatively complex projects and so is a hub for high-specification rig activity. Overall, the results in this section underscore the importance of accounting for not just *how much* capital leaves but also *what kinds* of capital leave after a change in regulation.

7.3.2 Decomposition of the change in profits

To further understand the role of capital misallocation in the main findings, I decompose the change in profits for each counterfactual in Table 6. 'Private misallocation' is the change in profit that would occur between the baseline and counterfactual keeping costs fixed but relocating capital. That is, it captures changes in profit due to equilibrium capital relocations: to escape the regulation, capital moves to less profitable locations. These locations may be less profitable because there are fewer matches, due to higher costs $c_{l,y}$, or if the type of capital is a bad match for the distribution of demand $f_l^{entry}(x)$. The 'direct effect' is the mechanical change in profits due to an increase in costs which I measure holding fixed the counterfactual number of matches in each location. I also report the share of each of these two effects in terms of the total change in profits.

Turning to the results in Table 6, a US-only increase in standards results in (private) misallocation of around 3.1% of global profits due to capital relocation. The cost of the standards themselves accounts for around a 3.3% decrease in global profits. As more areas become regulated, moving to the coalition counterfactual and then to global regulation, both the direct and indirect effects increase in total. However, the direct effect due to the regulation increases much more rapidly. The reason is the as regulation becomes more complete, capital relocation becomes relatively less profitable and there is less leakage. Hence, more rigs remain in their current (newly regulated) locations. This leads to a higher share of the change in profits occurring due to the regulation itself, rather than from moving to less profitable locations.

[33]The full equilibrium effects are explained in Section 4.5.1.

Figure 6: Profit change decomposition into misallocation and regulation cost

Counterfactual	**(Private) Misallocation**		**Direct Effect**		**Total**
	Change	Share of Total	Change	Share of Total	
US-only ↑ standards	-3.1	48.8	-3.3	51.2	-6.4
Coalition ↑ standards	-4.2	34.1	-8.2	65.9	-12.4
Global ↑ standards	-5.3	26.1	-15.0	73.9	-20.3

Note: The total change in global profits decomposed by private misallocation and a direct effect. Private misallocation is computed as the change in profits between the baseline and counterfactual at the pre-regulation costs. The direct effect of the regulation is the remaining change in profits.

7.4 Robustness

I test the robustness of the model to several alternative assumptions in Table 7a.

I first test the effects of a 10% increase and a 10% decrease in the costs of the regulation, reported in the second and third columns of Table 7a. An increase in costs decreases the welfare change of the regulation across the counterfactuals, and a decrease in costs increases the welfare change. However, the main conclusion that global regulation is more effective than more patchwork changes in standards is preserved.

I next test the effects of a change in the benefits of the regulation, considering a 10% increase and decrease in the benefits of the regulation (in terms of risk reduction of oil spills). Again, the absolute numbers change (for instance, increasing the benefits of the regulation increases the social welfare of introducing it in the counterfactuals), but the conclusion that coordinated regulation is most effective remains.

I also test the effects of alternative assumptions about the social cost of an oil spill in different locations in Table 7b. This robustness test is motivated by the fact that the social cost per barrel of oil spilled may be different in other regions than the US. Essentially, I ask: by ignoring leakage (which is the typical approach to cost-benefit analysis undertaken by US regulators in the oil and gas industry), what are we implicitly assuming about the social cost of polluting in other locations? The first exercise I perform is to find the social cost in non-regulated locations

Table 7: Robustness

(a) Alternative assumptions about the regulation

Counterfactual	**Model**	**Reg. Cost**		**Reg. Benefits**	
		-10%	+10%	-10%	+10%
US-only ↑ standards	3.2	6.7	0.7	0.2	6.4
Coalition ↑ standards	4.3	8.6	-3.0	-2.8	11.6
Global ↑ standards	25.3	34.5	21.0	11.6	39.3

(b) Alternative assumptions about social costs

Counterfactual	**'No leakage' equivalent social cost/barrel**		**'No location worse off' equivalent social cost/barrel**	
	Dollars	Δ% from US	Dollars	Δ% from US
US-only ↑ standards	3021	-18.4	1536	-58.5
Coalition ↑ standards	2887	-22.0	1514	-59.1
Global ↑ standards	3700	0	3700	0

Table (a): 'Reg Cost' refers to a change in the cost of the regulation. 'Reg. Benefits' refers to changes in the reduction in oil spill risk from the regulation. Table(b): This table explores alternative assumptions about heterogeneous social costs of an oil spill in different locations. It contains the results of the exercise 'what is the social cost of an oil spill in non-regulated locations where leakage can be ignored?'. The first column contains the social cost that would leave non-regulated locations no worse off on average after each counterfactual. The second column contains the percent decrease of this social cost compared to the US social cost (which is \$3700). Note that a global increase in standards makes all locations better off and so this row just contains the social cost in the US. The third column contains the maximum social cost for non-regulated locations which would leave them all better off for each counterfactual, and the fourth column converts this to a percentage change from the US value.

that would leave these locations no worse off on average.[34] In other words, it is the social cost where the leakage benefit from an increase in profits exactly equals the leakage cost of more oil spilled in these locations. At this social cost, the regulation will be as effective in increasing global welfare as the effects only considering the regulated markets.

I find that it would require a social cost assumption for non-regulated markets of \$3021 per barrel spilled - which is 18.4% lower than the US social cost - to ignore leakage in the US-only increase in standards counterfactual. For the coalition counterfactual the assumption would need to be even stronger at \$2887 per barrel, or 22.0% below the US social cost. For the global increase in standards all locations are better off. These number suggest that for a wide range of social cost assumptions leakage remains an issue and reduces the effectiveness of regulation.

Simply doing this exercise using average welfare misses the fact that leakage may still be doing considerable harm to some regions even if it is welfare-neutral on average, raising equity concerns. Therefore, I perform a second exercise which considers the minimum social cost assumption where no other regions would be worse off after the regulation. I find that this would require an even more extreme assumption of social costs in non-regulated areas at around \$1500 per barrel or almost 60% below the US social cost to ignore leakage in the US-only and coalition counterfactuals. This result is driven by poorer regions, particularly the Central Americas region. Again, this test suggests that for a wide range of social cost assumptions, ignoring leakage will tend to overstate the benefits of patchwork regulation.

8 Conclusion

Incomplete regulations are ubiquitous. A common concern is that after a change in the relative stringency of regulation economic activity will simply relocate to unregulated regions, resulting in spatial misallocation and undercutting the benefits of the policy. Despite large literatures that study incomplete regulation at an aggregate level, much less is known about the exact mechanisms by which incomplete regulation affects markets in specific settings. In this paper I build a spatial matching model to shed light on how incomplete regulation operates through the capital relocation channel in a decentralized factor market. The model extends the literature on spatial matching models in industrial organization to incorporate two-sided vertical

[34] That is, for social cost assumptions below this number, locations receiving the leakage will be better off.

heterogeneity of firms. Thus, the model can account for not just how much capital will leave after a change in regulation but also *what kinds* of capital will leave. I apply the framework to a previously unexplored dataset of contracts and relocation decisions in the market for offshore deepwater drilling rigs - an outstanding example of a decentralized capital market with patchwork policies. I find that incomplete regulations induce large changes in the geography of oil production through rig relocations. This relocation undercuts the environmental benefits of regulation, causing oil to be produced and spilled elsewhere in the world. The findings suggest that coordinated regulation might be preferred to patchwork policies.

Overall, this paper has focused on the medium-run effects of differences in regulation in the global oil and gas industry. In practice, over a period of many years, there are also likely to be longer-run effects. For example, informational externalities produced from the continued exploration of these oil fields, and the agglomeration of well-services industries nearby large fields, would also be affected by a decrease in drilling activity. Over a very long period of time these effects might exacerbate the effects of incomplete regulation, causing decreases in demand and further rig relocations out of regions with stricter regulation. It would be interesting to explore these effects in future work.

Finally, two-sided vertical heterogeneity is relevant in many other location-choice and matching decisions. For example, it is present in many other markets for physical capital such as heavy machinery. More broadly, sorting patterns and location decisions are present in other settings like labor markets. A fruitful direction for future work may be to apply the framework provided in this paper, with appropriate adjustments for context, to study misallocation in other settings.

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Appendices

A Engineering model for oil spills

I require a model that maps the number and type (i.e. the complexity) of the wells in each location into an expected total number of barrels spilled. Specifically, for a well of complexity x in location l, I require the following mapping:

$$\text{spill}_l(x) = \text{standards}_l \times \text{spill per barrel produced} \times \text{production}(x) \tag{15}$$

Here, standards_l is the stringency of drilling standards in location l which modifies the total amount spilled (I detail in the main text how these values are chosen). Mapping total oil production into an expected spill per barrel and then assuming a risk modifier based on the regulation in the market is essentially the existing approach taken by the US regulator (the BOEM) that is used to produce official reports about the expected costs and benefits of new offshore technology, the leasing program, and other regulations: BOEM (2016). Therefore I need the following two components (plus values for standards_l):

1. A model that maps well complexity into oil production
2. An engineering model that maps oil production into the expected number of barrels spilled.

For the first model, I run the regression:

$$\text{oil production}_i = \beta_0 + \beta_1 \text{well complexity}_i + \epsilon_i \tag{16}$$

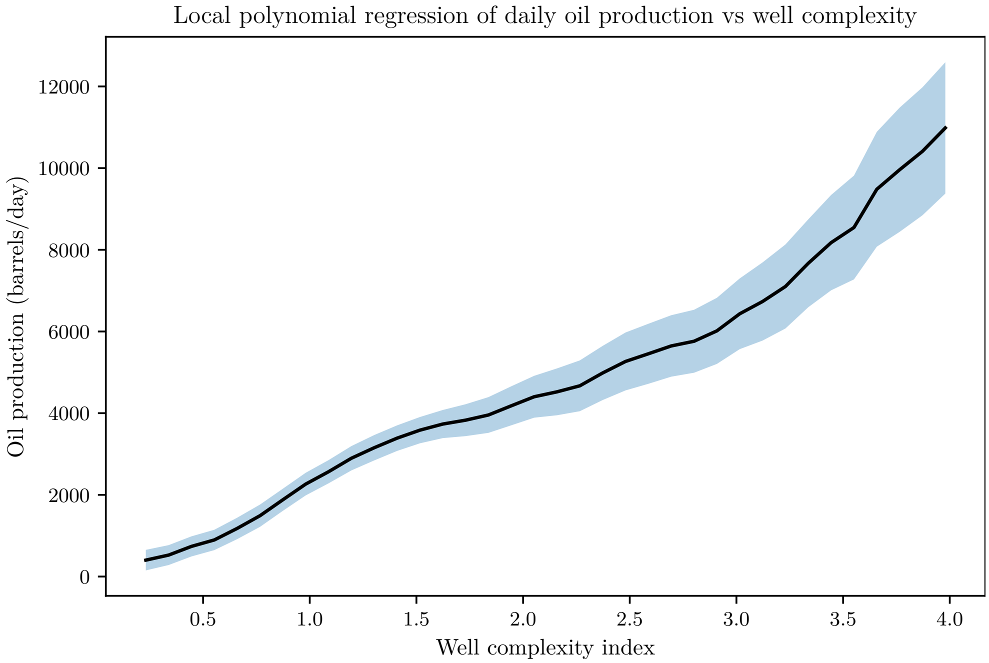
which exploits the strong relationship between complex wells and increased oil production. The results from this regression are $\beta_0 = 19.5(594.35)$ and $\beta_1 = 2088.4(243.42)$ (standard errors in brackets) and the sample size is for 382 wells where there is both production and well complexity data. I plot a local polynomial regression of this relationship in Figure 7.

For the second model, I use an engineering model used in studies by the US regulator: e.g. BOEM (2016). A challenge to constructing a model of oil spills is that they are typically 'rare events', which makes controlling for many factors difficult. The BOEM model uses historical data on the probability of a blowout and fits the following model that predicts the spill size per-well:

$$\mathbb{P}(\text{spill size} = q) = 0.00099q^{-0.24078} \tag{17}$$

The analysis predicts that at around the long-run average oil price (a 'mid-price' scenario) which includes drilling 3312 wells in the US Gulf of Mexico, 817100 barrels of oil are expected to be spilled over the lifetime of the leasing program. The study also estimates 5668 million barrels oil will be produced. This results in a figure of around 0.000144 barrels spilled per barrel produced in the US Gulf of Mexico.

Figure 7: Relationship between oil production and well complexity



Note: Shaded area is the 95% confidence interval.

The number of barrels spilled per-barrel outside the Gulf of Mexico depends on environmental standards in different markets. Studies have focused on estimating the risk reduction from changes to standards in the US in 2016, which aimed to increase drilling standards in the US to a level that is closer to the 'North Sea Standards' in Europe. As I elaborate on in Section 7.2, I therefore split markets up into to groups: Europe which has 'North Sea Standards' and the rest of the world, which does not.

B Data construction

I use several datasets for the analysis:

- Rigzone data of rig status updates and contracts
- Permit, borehole, and production data, from the BSEE (Bureau of Safety and Environmental Enforcement)
- CERDI dataset of bilateral distances between locations

I explain first how I clean the raw Rigzone data. I then explain how I perform a merge between the BSEE data and the Rigzone data to get the data on contracts and details of the projects under each contract in the US market. Finally, I explain how I construct key metrics from the cleaned data like rig utilization.

B.1 Cleaning the Rigzone data

As mentioned in the data section (Section 2.2), offshore drilling can be split into two broad categories. The first category is shallow-water drilling which is undertaken in water depths of less than 500ft using 'jackup' rigs which extend their legs to the seabed. The second category is deepwater drilling with is undertaken in water depths of more than 500ft using 'floater' rigs (drillships and semi-submersibles) which anchor themselves to the seabed but can drill in over 10000ft of water. These two categories of drilling are treated by practitioners as essentially separate markets. This is due to, for example, the differences in rig technology, and the fact that the oil and gas wells drilled by rigs in the deepwater are typically much more complex, costly, and productive, than wells in shallow water. In this paper I cut the data just to the deepwater market for the years 2005-2016 where the number of contracts per year appears to be relatively stable: see Section D for the number of contracts in the dataset over time.

Although most rigs operate under relatively short-run contracts, a small number of rigs operate under extremely long-run contracts for a single oil company (e.g. a 10 year contract). I delete rigs that operate under contracts that are longer than 2 years, treating these very long-run contracts as essentially a different type of market than those deepwater rigs which perform short-run work. Specifically, I delete 213 contracts that are longer than 2 years, comprising 10.9% of the total number of contracts (and reducing the total number of contracts from 1953 to 1740).

B.2 Merging the Rigzone data with the BSEE data

Critical to my estimation strategy is data that links rig and well characteristics to contract prices (and other contract details). In the US market I have data on both well characteristics (from the BSEE) and contract details (from Rigzone). In this section I describe how I merge these two datasets.

I begin with a dataset of 322 contracts for the US market, and 741 wells. I successfully match 462 wells, and collapse these contracts to 145 matched contracts (many contracts contain multiple wells and for these cases I use the average complexity of the matched wells), which I use for the auxiliary regression in the model estimation. Note that for the graphs in Figure 3 I use the full sample of wells not just the matched subsample (since the permit data has the maximum drilling depth of the rig in it, and I do not require prices to draw these graphs). Also note that for many metrics such as average prices, utilization etc, I do not require the matched contracts and so where possible I use the full sample of contracts.

B.3 Constructing metrics

In this subsection I describe how I construct metrics that I use in the estimation from the cleaned Rigzone data.

Rig relocations I construct rig relocations simply by looking at changes in rig statuses (for example, a rig is in one region in one status and then in the next status it is in a different region). Typically, these relocations are that the rig is drilling in one region and then moves to drill in a different region. However, there are some exceptions to this. Notably, I include several movements from a shipyard (e.g. the rig is 'Under Construction' in Asia) to a different region (e.g. the rig is then 'Drilling' in USA) as a relocation. My justification for including this as a relocation choice is that these rigs could have alternatively just remained and drilled in the field in the region in which they were constructed (my definition of a region is large enough that it is always a possibility that this could occur) or potentially could have chosen to move after construction to a different location. Therefore, I assume that these relocations contain useful information about the relative costs and benefits of drilling in different locations and so include them in the relocation data.

Rig utilization Rig utilization is defined as the average proportion of time that a rig is under contract. Since the model is computed at the monthly level, I first aggregate the dataset to a monthly rig status dataset. In this aggregated dataset I count the number of new contracts and multiply this by six months (approximately the average length contract) to get the total months under contract in each region. To get the number of 'marketed rigs' in each location I also need to measure the number of unmatched but available rigs. To do this, I count rigs as 'marketed' if they either received a new match or if the rig is either in the status 'Ready Stacked' (staffed and ready to drill with little delay) or if it is moving between regions. If a rig is moving between regions then I assume that the rig spends one week of the move in the current region and the remainder of the month travelling or arriving in a different region. Implicit in this definition of 'marketed rigs' is that I do not count rigs that are in the statuses 'Cold Stacked' (mothballed), 'Maintenance' (undergoing routine maintenance) or 'Inspection' (undergoing a routine inspection to ensure they are in working order), in the utilization metric. In other words, the utilization definition is for the number of 'effective' rigs in each location (those rigs not undergoing routine maintenance or inspections which imply they cannot drill).

I use the above procedure to compute the moments to estimate the model which, for computational reasons, approximates the market by modeling rig location and matching choices as occurring at a monthly level. To produce the figures about the effects of the 2010 moratorium in Figure 2 I use more disaggregated daily data. There are two notable additional steps that I take to compute utilization and the number of rigs in the US Gulf of Mexico in Figure 2, due to the unusual circumstances of the moratorium.

First, many contracts were cancelled using 'force majeure' provisions after the moratorium; outside of the moratorium I observe no other instances of cancelled contracts in the data. To deal with these cancellations, I only count when the rig's status was actually drilling as when it was 'utilized', rather than using the length of the full contract.

Second, I include when a rig is under the statuses 'Maintenance' and 'Inspection' to produce the utilization and the net exit figures in Figure 2 (specifically, I count a rig as 'utilized' and in the US market if it is being inspected or under maintenance). For computing the moments, these rely on the *average* utilization in a region and the proportion of rigs being inspected or maintained is relatively stable over time outside the moratorium. However, in the months after the moratorium and possibly as a consquence of the Deepwater Horizon spill, many rigs were inspected or under maintenance at once. Therefore, if I were to remove these statuses, it would tend to make it appear that many more rigs were not in the US in the months after the moratorium, when they were actually just under maintenance or inspection.

C Algorithms

C.1 Algorithm for computing the supply-side equilibrium

For a guess $\mathbf{c}$ of the parameters I can compute the predicted choice probabilities using the following algorithm:

1. Guess initial value functions $V^0_{l,y}(\mathbf{c})$ and the value of unemployment $U^0_{l,y}(\mathbf{c})$.
2. Iterate the following equations to recover the ex-ante value of searching in each location $V_{l,y}(\mathbf{c})$:

$$U^{k+1}_{l,y}(\mathbf{c}) = \sigma_\epsilon \log\left(\sum_{l'\neq l} \exp\left(\frac{-c_d d_{l,l'} + \beta V^k_{l',y}(\mathbf{c})}{\sigma_\epsilon}\right) + \exp\left(\frac{\beta V^k_{l,y}(\mathbf{c})}{\sigma_\epsilon}\right)\right) + \sigma_\epsilon \gamma^{euler} \tag{18}$$

$$V^{k+1}_{l,y}(\mathbf{c}) = \lambda_{l,y}\left(\sum_{s=0}^{\tau-1} \beta^s(\bar{p}_{l,y} - c_{l,y}) + \beta^\tau V^k_{l,y}(\mathbf{c})\right) + (1-\lambda_{l,y})U^k_{l,y}(\mathbf{c}) \tag{19}$$

   Here $\lambda_{l,y}$ is the empirical probability of a type y capital finding a match in location l, and I use the empirical average price $\bar{p}_{l,y}$.

3. Compute predicted choice probabilities for moving from location l to l' using $V_l(y|\mathbf{c})$ and Equations 7 and 8.
4. Compute the likelihood:

$$L = \sum_y \sum_i \sum_j logP(i|j, y, \mathbf{c})^{n_{yij}} \tag{20}$$

The value n_{yij} is the number of observations (i.e. months) that I observe a type-y capital move from location l to location l'.

5. Maximize the likelihood L over $\mathbf{c}$.

C.2 Algorithm for computing the demand-side equilibrium

Using the rig costs from the first step of the estimation, the empirical total number of rigs in each location $n_{l,y}$, and a guess of the match value parameters and the demand parameters, I compute an equilibrium as a fixed point in the probability a project matches with each capital type $\{q_{l,y}^{project}\}_{y\in\{low,mid,high\}}$.

I use the following algorithm:

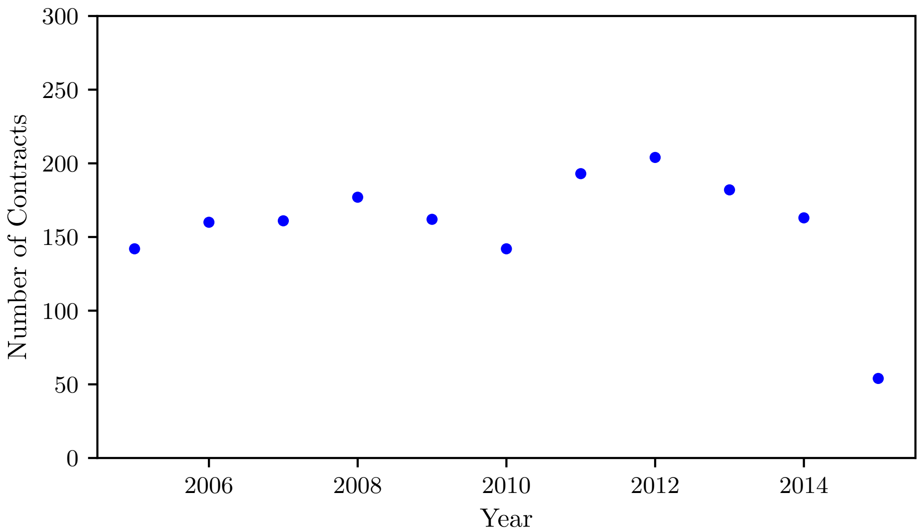
1. Guess the matching probability $\{q_{l,y}^{project,k}\}_{y\in\{low,mid,high\}}$ where k denotes the iteration and $k=0$ denotes the initial guess.
2. Note that since rig costs are known, and for a guess of the other parameters, I can compute prices using the Nash Bargaining solution. Therefore, I can compute the value of a project of type x targeting a rig of type y using Equation (1): $\Pi^{project}(x,y)$.
3. Using these $\Pi^{project}(x,y)$, update the guess of $\{q_{l,y}^{project,k}\}_{y\in\{low,mid,high\}}$ using a matching simulation (for each location, draw wells from a poisson distribution, match these wells with rigs using the targeting probabilities $s_{l,y}$, update the backlog of each rig, and then repeat this exercise many times).
4. Iterate from Step 2 until convergence.

C.3 Algorithm for computing the counterfactuals

I compute the counterfactuals with the following algorithm.

1. Initialize with empirical average prices $\bar{p}_{l,y}^{k}$ and the empirical probability of matching $q_{l,y}^{capital,k}$ at iteration $k=0$.
2. Compute the supply side equilibrium value functions and relocation choices using the supply side algorithm in Appendix (C.1).
3. Compute the stationary distribution of available rigs given relocation choices and the probability of matching in each location. Denote the number of available rigs at iteration k by $n_{l,y}^{k}$.
4. Compute the demand side equilibrium using the demand side algorithm in Appendix (C.2). Recompute and update average prices $\bar{p}_{l,y}^{k+1}$ and the probability of matching $q_{l,y}^{capital,k+1}$.

Figure 8: The number of contracts per year is relatively stable



Notes: This figure plots the total number of deepwater drilling contracts in the data from 2005-2016. The dataset ends mid-2015 and so the number of contracts I have for 2015 is less than for other years (i.e. if the data stretched to the end of 2015 I would expect the total number of contracts to be roughly equal to other years). The fact that the number of contracts is relatively stable over these years motivates modelling the market as in a steady-state equilibrium without aggregate shocks.

5. Return to Step 2 and continue to iterate until the stationary distribution of available rigs converges.

D Additional tables and figures

Table 8: Fit of the moments: simulated vs data

	Simulated	**Data**		**Simulated**	**Data**
US			**Australia**		
Av. Price: Low	0.24	0.24	Av. Price: Low	0.3	0.27
Av. Price: Mid	0.32	0.33	Av. Price: Mid	0.38	0.33
Av. Price: High	0.42	0.43	Av. Price: High	0.55	0.5
Utilization	0.93	0.94	Utilization	1.0	0.98
Av. complexity: Low	1.22	1.19	**Central Americas**		
Av. complexity: Mid	2.82	2.75	Av. Price: Low	0.26	0.23
Av. complexity: High	3.83	3.84	Av. Price: Mid	0.44	0.45
$\beta_{0,low}$	0.3	0.28	Av. Price: High	0.56	0.53
$\beta_{0,mid}$	0.39	0.41	Utilization	0.83	0.85
$\beta_{0,high}$	0.45	0.4	**Europe**		
β_1	-0.07	-0.05	Av. Price: Low	0.32	0.32
β_2	0.07	0.06	Av. Price: Mid	0.46	0.40
Africa			Av. Price: High	0.48	0.51
Av. Price: Low	0.31	0.3	Utilization	0.97	0.96
Av. Price: Mid	0.34	0.35	**Mediterranean**		
Av. Price: High	0.44	0.49	Av. Price: Low	0.28	0.21
Utilization	0.9	0.88	Av. Price: Mid	0.39	0.38
Asia			Av. Price: High	0.45	0.45
Av. Price: Low	0.26	0.23	Utilization	0.89	0.9
Av. Price: Mid	0.34	0.33	**South America**		
Av. Price: High	0.51	0.48	Av. Price: Low	0.29	0.24
Utilization	0.8	0.8	Av. Price: Mid	0.34	0.28
			Av. Price: High	0.45	0.47
			Utilization	0.96	0.97

Note: This table shows the fit of the simulated moments vs the empirical moments in the data. The simulated method of moments procedure is performed independently for each location starting with the US market.