Capital Reallocation and Incomplete Regulation: Evidence from the Offshore Oil and Gas Industry

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Abstract

I examine how capital reallocation impedes the effectiveness of incomplete regulation. I develop a framework of a decentralized capital market which extends the location choice and dynamic matching literature to a setting with two-sided vertical heterogeneity leading to sorting. I apply the framework to a novel dataset of contracts and projects in the global market for deepwater oil and gas rigs. I quantify how different designs of supply-side environmental policies cause leakage within and across space, and misallocation. Policy designs that do not account for capital reallocation are relatively ineffective and, in some cases, can even increase global emissions.

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1 Introduction

Using local regulation to solve global problems — known as incomplete regulation — is ubiquitous. A prime example is the worldwide response to climate change, which lacks a coordinated agreement and instead consists of a patchwork of regional policies. A growing concern is that this uncoordinated action can cause 'leakage' when economic activity moves to locations or sectors with weaker regulation. Central to these debates and policy design is understanding the exact channels by which leakage takes place.

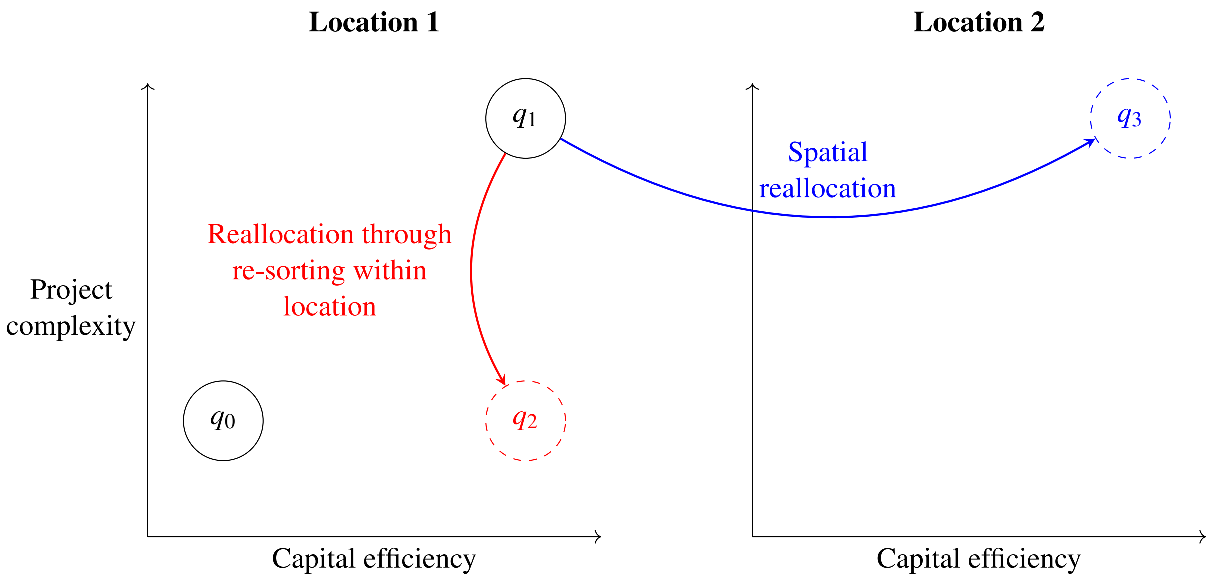
The empirical literature has primarily focused on leakage through a product market channel. Here, local regulation raises the relative price of tradeable goods, leading to increases in production and emissions elsewhere.[1] In contrast, theoretical work emphasizes a second channel: physical capital reallocation.[2] Here, local regulation decreases the profitability of local capital inputs, which causes capital to reallocate to unregulated markets; this decreases the price of inputs elsewhere and spurs production. However, less is known about the empirical relevance of this channel and the implications for policy design. A key blocker to empirical progress is that data on markets for physical capital (such as contracts between firms, prices, and allocations) are typically confidential.

This paper exploits an unusually detailed dataset of contracts and capital movements in the global market for deepwater drilling rigs to quantify leakage that occurs in decentralized capital markets. I focus on markets where physical capital needs to match with projects to produce output. In these markets two-sided vertical heterogeneity leading to sorting may be first-order: heterogeneous capital may reallocate towards unregulated markets with the greatest complementarities. Moreover, policies may disproportionally target certain types of projects, causing capital to reallocate towards projects and locations with less complementarities than the regulated market, generating misallocation. I illustrate these channels in Figure 1.

[1] Examples in industries such as electricity, cement, and oil and gas, include Abito, Knittel, Metaxoglou and Trindade (2022), Fowlie and Reguant (2018), Fowlie, Reguant and Ryan (2016), Prest (2022), Prest and Stock (2023).

[2] Theoretical work includes Baylis, Fullerton and Karney (2013).

Figure 1: Capital reallocation channels



Note: This figure illustrates two channels for how capital reallocation generates leakage in the presence of two-sided vertical heterogeneity. Here, there are two pieces of physical capital (in this paper, these are drilling rigs): one high-efficiency and one low-efficiency. Initially there are two matches in location 1: the high-efficiency capital is allocated to a complex project q_1 and the low-efficiency capital is allocated to a simple project q_0. Consider the effects of a ban on drilling complex projects in location 1. The direct effect is to eliminate the match q_1. However, capital may reallocate to q_2, where it is less well-matched within location 1. Or, it may reallocate across space to a complex project in location 2.

Overall, this paper answers the questions: how important is the capital reallocation channel, and would more complete regulation improve outcomes? To do so I develop a new empirical framework to study capital reallocation within and across space that extends the location choice and dynamic matching literature in industrial organization to a setting with two-sided vertical heterogeneity in matches leading to sorting. I apply the framework to the market for deepwater drilling rigs. I study the central role of capital reallocation in how proposed 'supply-side' climate policies (policies that restrict the production of oil and gas) affect profits and carbon emissions.

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 a movable form of capital: drilling rigs.[3] Offshore oil rigs are 'marine vessels' that are explicitly

[3]Counting both onshore and offshore production, this industry generated $6.6 trillion in revenue in 2022. (`https://www.ibisworld.com/global/market-size/global-oil-gas-exploration-product`

designed to be easily transportable between locations. 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 industry has recently been the target of proposed 'supply side' regulations designed to restrict the production of oil and gas. For example, the Biden Administration has dramatically — and controversially — reduced the number of offshore drilling leases for sale in the US market because of the climate effects of the oil and gas which will be produced and consumed from the resulting wells (Friedman (2023)).[4]

The market is shaped by geographical space: oil field locations are situated across the world and rig owners must choose the most profitable location for their capital. It is also shaped by two-sided 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 complementarities matter, with more efficient rigs sorting towards more complex projects.[5] Furthermore, different locations contain different types of projects. For example, the South American market is known to have oil and gas fields with complex projects involving deep or high-pressure wells. This market therefore attracts relatively more efficient rigs than other locations.

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. The 2010 moratorium was a particularly stark example of incomplete regulation: while drilling was

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[4]In economics, supply-side climate policies have been analysed theoretically in Harstad (2012), amongst others. Across the world there are numerous similar proposed policies; a useful summary is detailed in Ahlvik, Andersen, Hamang and Harding (2022). Overall, the idea behind these policies is that they directly change the total amount of production in the regulated area. Since oil and gas are globally traded commodities, given the global elasticity of demand for hydrocarbons and also the elasticity of supply for the rest of the world, decreases in supply in a subset of the world market can be scaled up to a total change in the equilibrium global quantity of hydrocarbons produced and consumed. This equilibrium change in consumption can then be converted into a change in carbon emissions using engineering estimates.

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

temporarily halted in the US market, it was allowed to continue 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 countries such as Brazil, where they could continue to drill.

Motivated by this illustrative example, I estimate a model of the global deepwater drilling market using data on the positions and status (including information about contracts) of all deepwater rigs worldwide between 2005-2016. In the model there are several spatial locations worldwide (oil fields). Locations differ by demand (potential projects), as well as costs relating to the operational expenditures of the rig owner (e.g. salaries and accommodation for the rig crew). 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.[6]

In 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. Key to this decision is the quality of potential matches for each particular capital type in each location.

I use the model to test several counterfactual policies. These center around proposed 'supply-side' policies that limit both the type of wells and also the number of wells that can be drilled in a location. The first set of counterfactuals consider a ban on very complex wells. This counterfactual corresponds directly to drilling bans in the industry like the 2010 US moratorium, which target deepwater wells that are usually the most complex to drill but also tend produce the most hydrocarbons. It also serves as a good proxy for proposed bans which correspond to sales of *new* offshore leases such as those implemented by the Biden Administration.[7]

[6] 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.

[7] Over time drilling has broadened to geological formations which are more difficult to drill. Therefore, these new leases tend to correspond to more complex wells than existing leases. For a history of the industry and changes in leasing patterns see Gramling and Freudenburg (2012).

I test the effects of moving from incomplete regulation (a US-only ban), to more complete regulation (a coalition of richer countries incorporating the US, Europe, Australia, and South America), and finally to a global ban. Leakage from a US-only ban through the capital reallocation channel is substantial. For every ton of carbon dioxide saved through banning complex wells, within-location capital reallocation generates 0.24 more tons, while an additional 0.19 tons are generated through reallocation across space to unregulated locations.[8]

Although a coalition of rich countries may be a politically feasible means of increasing the size of the regulated area, leakage is still relatively high. Overall, capital reallocation limits the reduction in emissions by -33.7 percent. The reason leakage remains high is because this coalition fails to account for match complementarities. Specifically, complex well bans cause high-specification rigs — which have the greatest matching complementarities with complex wells — to disproportionally leave for markets where the demand for drilling complex wells is high but are not regulated, like Africa.

A global ban would be slightly more effective, eliminating leakage across space. However, all these options would still be costly due to capital misallocation: incomplete regulation generates misallocation across space, but complete regulation generates misallocation primarily through its effect on sorting within locations. For example, high-specification rigs who were previously matched to complex wells re-target and match to wells with less complementarities.

Next I test a ban on drilling simple wells. This corresponds to an extreme version of the current policy emphasis in the US market, which favors drilling more complex wells.[9]. Here I find that leakage numbers are even higher for US-only regulation than in the complex well ban case.

A coalition of rich countries imposing a ban on simple wells would eliminate spatial leakage

[8]Although wells produce both oil and natural gas, which both result in carbon emissions once consumed, this paper focuses only on the emissions from burning the oil content and not the natural gas content. The rationale is that deepwater wells are predominately in fields where the hydrocarbon content is mainly oil. Furthermore, the chemistry of burning natural gas results in relatively less emissions per energy unit than oil: `https://www.eia.gov/energyexplained/natural-gas/natural-gas-and-the-environment.php`. Overall, this implies the results are conservative.

[9]For example, the Deepwater Royalty Relief Act of 1995 provides large subsidies through 'royalty relief' suspensions to deepwater drilling operations: US Code Title 43.

of emissions. However, it accentuates within-location re-sorting of low-efficiency rigs towards complex wells, which produce more oil. Overall, this causes carbon emissions to *increase* as a result of the ban. A global ban on simple wells would similarly increase emissions.

1.1 Contributions

Overall, this paper makes three main contributions. The first is a new framework of location-choice and matching in a decentralized capital market which allows for two-sided vertical heterogeneity. This is a key difference to previous work using location choice models in, for example, bulk shipping and taxis, where agents are relatively homogeneous (e.g. Frechette, Lizzeri and Salz (2019), Buchholz (2022), Brancaccio, Kalouptsidi and Papageorgiou (2020)).

By contrast, in the offshore oil and gas industry, two-sided vertical heterogeneity is important. Capital owners need to take into account the *quality* of potential matches for their capital type. Furthermore, regulation (like banning complex wells) may target heterogeneous projects. Aggregating up individual relocation decisions to the global market results in rich equilibrium dynamics pictured in Figure 1, featuring both reallocation of heterogeneous capital across markets and also reallocation through re-sorting of matches within locations. Capturing this heterogeneity is essential to quantifying the effects of incomplete regulation in this setting.

The second contribution is the analysis of a detailed dataset of firm-to-firm contracts, movements, and projects, in a global capital market. As previously mentioned, these markets are typically difficult to study because micro-data on contracts and allocations are often confidential. At the same time, many types of physical capital are traded in decentralized markets (Gavazza (2016)). Moreover, movements of capital across space is thought to be a key method of capital reallocation more broadly (Ramey and Shapiro (2021)). The data provide a granular picture of the inner-workings of a real-world capital market.

The third contribution is a set of new findings about the efficacy of incomplete supply-side regulation with capital reallocation in a large global market: the offshore oil and gas industry.

1.2 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 electricity markets (Abito, Knittel, Metaxoglou and Trindade (2022)) and the cement market (Fowlie, Reguant and Ryan (2016)). In contrast to these papers which focus on how incomplete regulation operates through a production channel, this paper sheds light on the role of capital reallocation.

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 'footloose' industries using more aggregated data e.g. Ederington, Levinson and Minier (2005). Davis and Kahn (2010) finds that used vehicles that fail emissions testing in California are more likely to be exported to Mexico. Complementary to these studies, I study a particular industry to delve into a specific leakage mechanism: capital reallocation.

A third strand is research into the oil and gas industry e.g. Kellogg (2011), Asker, Collard-Wexler and De Loecker (2019). As well as the papers already mentioned, 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, and these data contain fewer covariates for the projects undertaken under each contract. Vreugdenhil (2023) 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 reallocation across oil fields in response to regulation.

Finally, as mentioned, this paper is related to a recent literature that estimates spatial matching models in industrial organization (e.g. Frechette, Lizzeri and Salz (2019), Buchholz (2022), Brancaccio, Kalouptsidi and Papageorgiou (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 two-sided vertical heterogeneity.

2 Market description and data

Offshore drilling is segmented into shallow water (< 500ft water depth) and deepwater drilling (> 500ft water depth). I follow 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 at the well site. This is in contrast to the shallow water market detailed in Vreugdenhil (2023) which uses Jackup rigs which extend their legs to the seabed.

Oil rigs are ships that move around the ocean drilling wells. Long-distance moves between fields (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. Figure 2 shows an example of a deepwater oil rig moving using a dry tow.

The process of drilling a deepwater well and procuring a rig is as follows. Oil companies like BP and Chevron lease areas 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. Since oil companies do not own the oil rigs they use to drill with, they need to match with an appropriate drilling rig. Oil rigs are rented under simple dayrate contracts for the time it takes to drill a well.[10] After the well is completed (around 6 months) it is typically

[10] 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.

connected to an undersea pipe for continuing extraction. The rig then moves on to its next job.

Drilling responsibilities are precisely delineated in this industry. While rig owners are responsible for furnishing the rig in good working order, and paying expenses for the salaries and accommodation of the crew onboard the rig, they do not pay for any of the drilling costs of materials. Instead, the oil company owns the well, is the beneficiary of selling the produced hydrocarbons, and bears responsibility for drilling expenses like materials. The oil company has a representative (called the 'company man') who lives on the rig and represents the oil company's interests.

Finally, the deepwater drilling industry is highly fragmented. Both the rig owner side and the oil company side of the global market are unconcentrated. Therefore, I do not allow for either side of the industry to exert market power in the model.

2.1 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 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 per day for a given duration and rarely contain performance incentives.

The data sample covers the years 2005-2016 and Table 1 provides summary statistics. 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 cyclical changes in oil and gas prices over this time.[11] Motivated by this fact I choose to model the market as in a steady-state equilibrium without aggregate shocks.

[11]For example, for a year at the start of the dataset with a moderate oil price (2006) the total number of contracts was 187; in the oil price bust in 2009 the number of contracts was relatively similar at 183; and, when the oil price return to a boom in 2011, the total number of deepwater drilling contracts was 188.

Figure 2: A deepwater drilling rig moving between locations

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.

Table 1: Summary Statistics

Variable	N	Mean	Std. Dev.
Daily Rig Activities (millions)	1.75		
Status Updates (unique)	5965		
Contract Price (millions USD/day)	1873	0.32	0.16
Contract Duration (days)	1873	170	154
Prob. of Relocation	964	0.5	0.25

Table 2: Summary Statistics: Heterogeneity

	Capital Type (Efficiency)		
	Low	Mid	High
Prob. of Relocation	0.38	0.42	0.71
Utilization	0.88	0.87	0.9
Dayrate	0.27	0.31	0.44
Average Match: Well Complexity	1.2	2.7	3.7

Although most rigs operate under relatively short-run contracts (around 6 months) and are rented over time by many different oil companies, there are a small number of rigs that operate continually under very long-term contracts. As a result, I delete rigs that operate under contracts of duration greater than two years. In total I have 5965 'status updates' for deepwater rigs, which amount to 1.75 million daily rig activities. I provide more detail about these status updates and the data cleaning steps in Appendix B.

Rig heterogeneity 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, and other factors. I aggregate capital heterogeneity into three types by maximum drilling depth and call these types 'low', 'medium' and 'high' specification rigs.

Table 2 describes some ways that these rig differences matter. High-specification rigs fetch higher prices than other rig types and also tend to relocate more frequently. However, all capital types have relatively similar levels of utilization.

Well heterogeneity Wells can be ranked in terms of how complex they are to drill using an engineering model called the 'mechanical risk index'. This index takes well covariates such as depth and bottomhole pressure, and ranks wells on a one-dimensional index of drilling complexity. I detail steps taken build this metric in Appendix B.3.3.

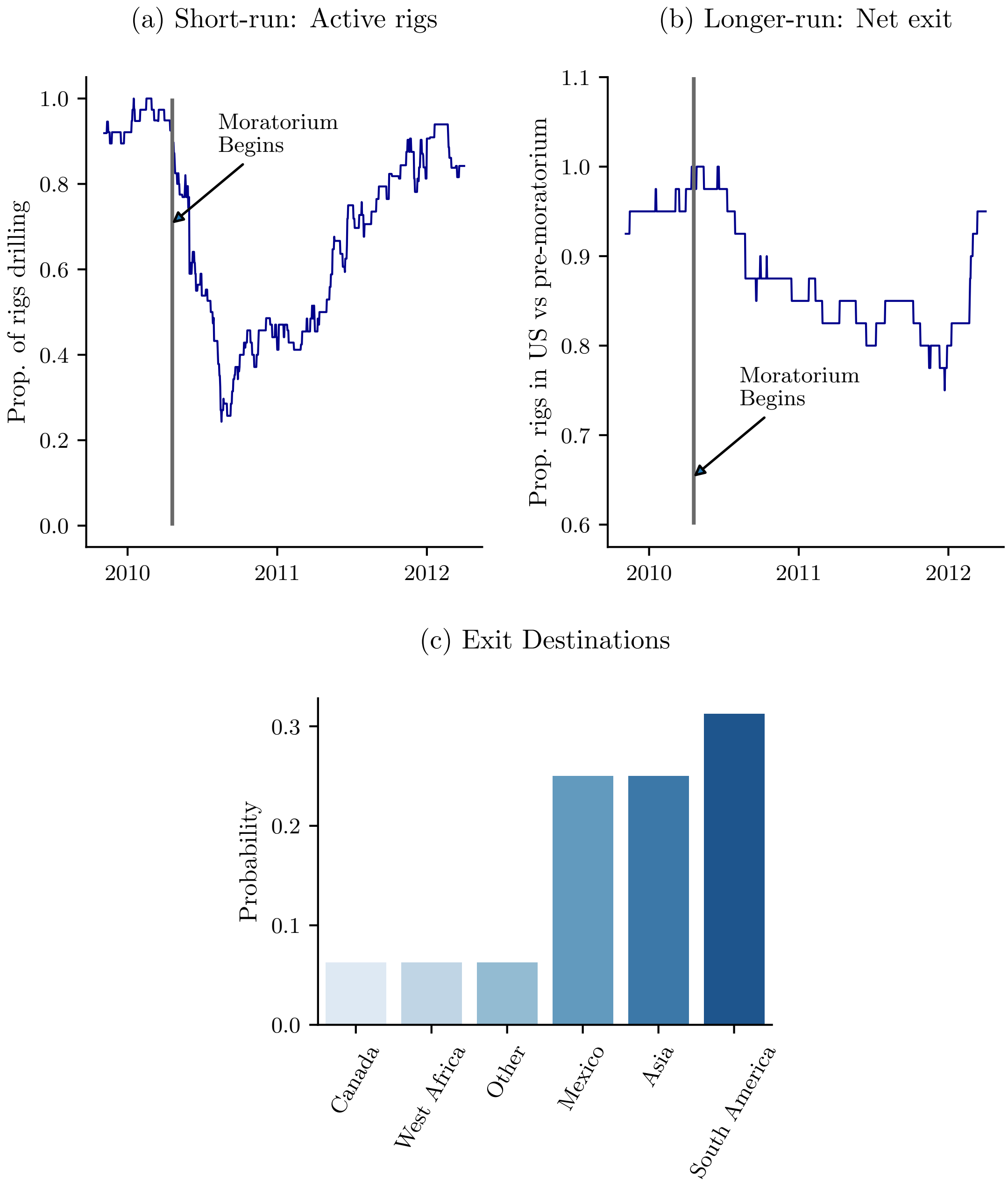
As is apparent in Table 2, more efficient rigs sort towards more complex wells. I describe these patterns in more detail in Section 3. In addition, more complex wells tend to produce more oil (and therefore more emissions when this oil is consumed). I detail these patterns, and the steps to map production into emissions, in Appendix A.

Location heterogeneity I aggregate capital locations into eight large regions across the world; within these regions the main oil fields are relatively close to each other.

3 Descriptive analysis of the deepwater rig market

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

Figure 3: Effects of the 2010 moratorium on the market for deepwater drilling rigs



Note: 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.

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.[12] 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.[13] 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)).

Figure 3(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, causing utilization 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 3(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, and I document the exact locations in Figure 3(c) . When the moratorium is lifted, rigs reenter the region. Overall, this shows that rigs are responsive to differences in regulation across markets.[14]

Observation 2: Positive sorting patterns suggest that match complementarities matter.

Figure 4 illustrates the sorting patterns between capital (rigs) and projects (wells) in the US market. Recall that we can rank wells vertically by their complexity using an engineering

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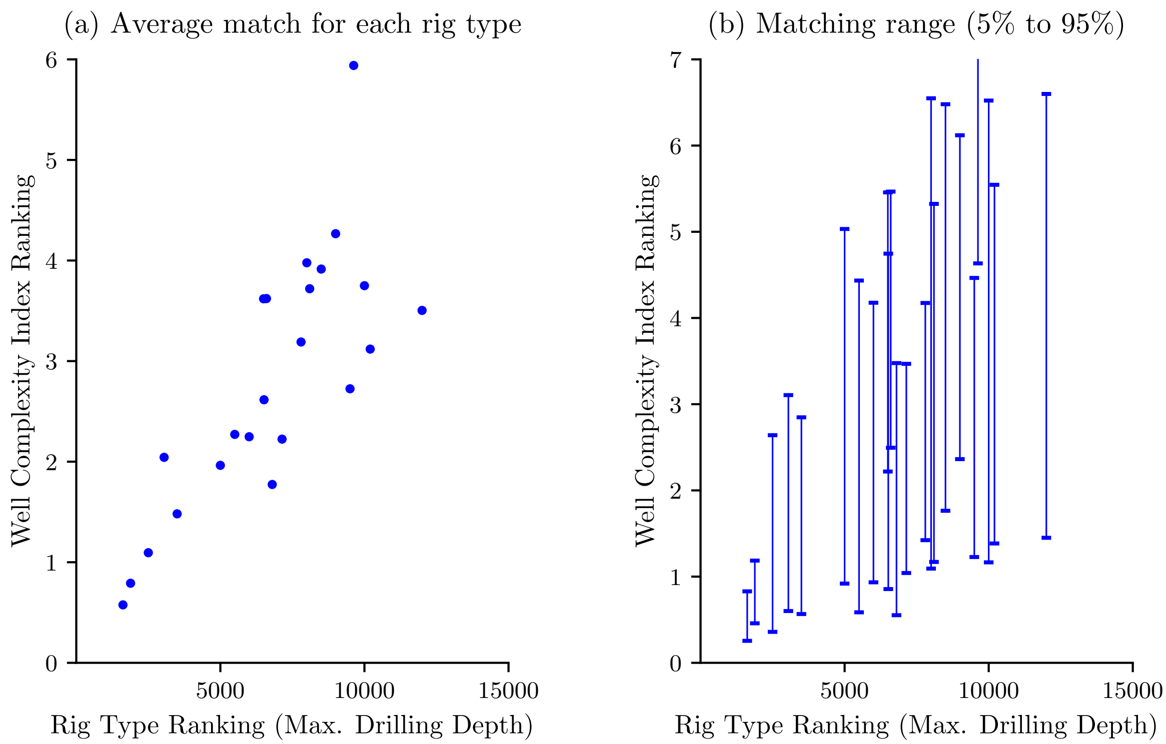
[12]Note that my main analysis incorporates information of *all* movements of rigs worldwide over a longer period of time to test the effects of regulation.

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

[14]Market analysts also 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)).

Figure 4: Sorting patterns for deepwater rig efficiency vs project complexity



Note: 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.

model called the 'mechanical risk index' and we can also vertically rank rigs by their efficiency (proxied by their maximum drilling depth). Figure 4 illustrates that more complex projects tend to match with more efficient rigs, both on average and over the entire distribution of project types.[15] These pictures suggest that match complementarities matter.

Where do these match complementarities come from in this industry? Broadly, more efficient rigs — through their better on-board technology — generate cost efficiencies once allocated to complex wells. For example, a complex well may involve drilling around a difficult geological formation, which involves a greater probability of risks like a "stuck pipe". The better technology of efficient rigs allows them to drill these difficult formations, and more readily deal with unexpected events as they occur. I further discuss complementarities in Section 6.

Different markets have different distributions of well complexity, which make them suitable for relocating different types of rigs. For example, the European market (the North Sea) is known to have relatively simple projects. Therefore, in the empirical distribution of rigs across the world, this region has proportionally more lower-efficiency rigs.

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. Denote the number of type-y rigs in location l by $n_{l,y}$. Each rig has a queue (a 'backlog') of projects and if the queue 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'.[16] The timing in each period within each location

[15] These sorting patterns are also apparent for shallow-water rigs Vreugdenhil (2023).

[16] 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.

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 a location-specific mean λ_l. The type of each of these potential projects is characterized by an independent draw from a distribution $x \sim f_{l,x}^{entry}$ of project complexity.

2. Targeting Each potential project knows its type x and chooses which kind of rig y to match with ('target').

3. Matching Within a period, potential projects match sequentially in the (random) order in which they are drawn with the capital type that they choose to target. If there are no more available rigs then unmatched potential projects immediately exit.[17] Otherwise, a match is formed.

4. Production 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. Prices are determined by Nash bargaining.

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

Discussion of key assumptions I now discuss two key assumptions in the model setup. First, I assume that agents make their decisions based on long-run averages in the market.

[17] 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.

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

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.

One justification for the above assumption — as previously mentioned in Section 2.1 — is that the deepwater market does not seem to be affected by current global oil and gas prices and so I do not allow for aggregate shocks. However, this 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, according to my data provider, contracts are eventually fully reported but there is often a delay, so the data are somewhat 'stale' and the current state of the marketplace is unknown at any point in time.

The second notable assumption is that agents can target their best match, and I do not allow for search frictions. Instead, I micro-found the matching process in the model through a queueing simulation that is tailored to the institutional details of the industry. If there is an available rig and it is being targeted by a potential project, then these agents will meet. Capital unemployment is generated solely due to the Poisson draws in demand: several successive low draws may result in rig unemployment. The 'no search frictions' assumption is different to previous work in other markets like taxis, 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 and so matching arguably involves fewer opportunities for frictions.

4.2 Demand: How projects match with capital

I first discuss the rig selection process for each potential project that enters. Since entry is exogenous, this is the only choice that projects make in the model. The ex-ante payoff to targeting capital of type y is:

$$\Pi_{l,x,y}^{project} = q_{l,y}^{project} \underbrace{\left(\sum_{s=0}^{\tau-1} \beta^s (m_{x,y} - p_{l,x,y}) + \varepsilon_y \right)}_{\text{Match value with type } y \text{ capital}} \tag{1}$$

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 i.i.d. extreme value. Note that I am suppressing individual project subscripts, but the ε_y is drawn independently for each searching project (as well as for each rig type y). A potential project contacts the capital type that offers it the highest expected value: $\max_y \left\{\Pi_{l,x,y}^{project}\right\}$.[19] Integrating over demand $f_{l,x}^{entry}$ the share of potential wells that target capital type y is:

$$s_{l,y} = \int 1\left[y = \underset{k}{\operatorname{argmax}} \left\{\Pi_{l,x,k}^{project}\right\}\right] f_{l,x}^{entry} dx \tag{2}$$

Since agents can target their best match, I assume that no matches are rejected (otherwise the project would have a negative payoff from entering the market).

I compute the probability of matching for projects and capital $q_{l,y}^{project}$, $q_{l,y}^{capital}$ that results from the above targeting decision using a matching simulation. I briefly discuss this simulation here and leave a more detailed description to Appendix C.2. Overall, I simulate a queue, for each rig type y, defined in Kendall's notation by $M/\tau/n_{l,y}/(n_{l,y}t_{backlog}/\tau)/FIFO$. That is, the queue has a Poisson arrival rate, service time at the contract duration τ, $n_{l,y}$ 'servers', $n_{l,y}t_{backlog}/\tau$ places in the queue, and a queuing discipline of first-in-first-out.

[19] 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.

4.3 Supply: Location decision

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

$$U_{l,y} = \max\left\{ \max_{l' \neq l}\{\underbrace{-c_d d_{l,l'} + \beta V_{l',y} + \sigma_\varepsilon \varepsilon_{l'}}_{\text{Value of moving to } l'}\},\ \underbrace{b_{stay} + \beta V_{l,y} + \sigma_\varepsilon \varepsilon_l}_{\text{Value to staying in location } l} \right\} \tag{3}$$

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, $\varepsilon_{l'}$ 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. Equation (3) delivers multinomial logit conditional choice probabilities for moving location which I later use for estimation; I provide more details about the exact form of these equations in Appendix C.1.

Using the location decision in Equation (3) I can write the ex-ante value function for unemployed capital (that is, the value function before the ε_l shocks are drawn):

$$U_{l,y} = \sigma_\varepsilon \log\left(\sum_{l' \neq l} \exp\left(\frac{-c_d d_{l,l'} + \beta V_{l',y}}{\sigma_\varepsilon} \right) + \exp\left(\frac{b_{stay} + \beta V_{l,y}}{\sigma_\varepsilon} \right) \right) + \sigma_\varepsilon \gamma^{euler} \tag{4}$$

where γ^{euler} is Euler's constant.

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

$$V_{l,y} = q_{l,y}^{capital} \underbrace{\left(\sum_{s=0}^{\tau-1} \beta^s \delta_{l,y} + \sigma_\varepsilon \gamma^{euler} + \beta^\tau V_{l,y} \right)}_{\text{Expected value to matching for the rig}} + (1 - q_{l,y}^{capital}) U_{l,y} \tag{5}$$

Here, $q_{l,y}^{capital}$ is the long-run average probability that capital of type y matches with a well in location l. The expected value to the rig of being in a contract in each period is $\delta_{l,y} =$

$\bar{p}_{l,y} - c_{l,y} + \xi_{l,y}$, where $\xi_{l,y}$ accounts for unobserved cost shocks.[20] The term $\bar{p}_{l,y}$ is the average price in location l for capital type y. The expected value of matching also includes the term $\sigma_\varepsilon \gamma^{euler}$ which is the expected value of the logit error if the rig is in location l; this value is also embedded in the value of unemployed capital $U_{l,y}$ if the rig does not match in Equation (4).[21]

4.4 Prices

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

$$\underset{p}{\operatorname{argmax}} \left[\sum_{s=0}^{\tau-1} \beta^s [m_{x,y} - p] - \beta(1 - P_{exit}) W_{l,x,y} \right]^{1-\eta} \left[\sum_{s=0}^{\tau-1} \beta^s \delta_{l,y} + \beta^\tau V_{l,y} - U_{l,y} \right]^{\eta} \tag{6}$$

Recall that prices are embedded in $\delta_{l,y} = p - c_{l,y} + \xi_{l,y}$. 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, η is the Nash bargaining parameter, and P_{exit} is an exit shock for unmatched potential projects. So, $1 - P_{exit}$ is the probability that the unmatched potential project does not exit and continues to search if the match is rejected. Note that this event occurs off the equilibrium path since all matches are accepted.

The value $\beta(1 - P_{exit})W_{l,x,y}$ is the project's outside option. For simplicity I assume that if a project rejects a match then it will target the same type of capital and so $W_{l,x,y}$ has a capital y subscript as well as the location l. The value $W_{l,x,y}$ is given as:

$$W_{l,x,y} = q_{l,y}^{project} \sum_{s=0}^{\tau-1} \beta^s (m_{x,y} - p_{l,x,y}) \tag{7}$$

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

[20] Note that I do not allow for unobserved demand shocks. This is mainly due to industry-specific reasons which suggest that such shocks are less important: for instance, as previously mentioned, the deepwater oil and gas industry is not substantially affected by oil and gas price cycles and the total number of contracts over the sample period is relatively stable.

[21] Another way of explaining the inclusion of this term is that when the rig is matched, it is implicitly choosing to be in location l and so should also receive a logit error shock.

happens with probability $1 - q_{l,y}^{project}$) then the project exits immediately since the backlog is too long, receiving a payoff of 0, and so this term disappears.

4.5 Quantifying oil production and emissions

I provide an overview here of how matches in the model are mapped into changes in global oil production and emissions, with the details presented in Appendix A. Wells produce both oil and natural gas in different quantities, and both result in carbon emissions once burned. This paper focuses only on emissions from burning the oil content. The reason is that deepwater fields predominately produce oil, and furthermore burning oil produces a far greater magnitude of emissions than burning the equivalent energy unit of natural gas.[22]

The complexity of an individual project is mapped into a production volume of oil using the empirical relationship that more complex projects tend to produce more oil. Then, given the equilibrium number and types of matches predicted by the model in each location, the model predicts a total volume of oil produced in the deepwater market.

I then convert changes in oil production in the deepwater market into a change in carbon emissions globally in two steps. First, I convert the change in supply from the deepwater market to an equilibrium global change in oil produced and consumed, incorporating demand responses as well as supply responses from non-deepwater fields. Second, I convert this global change in output to carbon emissions by scaling by the EPA's Greenhouse Gases Equivalencies Calculator.

4.6 Equilibrium

I formally define the equilibrium here. Note that rigs and project owners only internalize the private benefits and costs of their location choices and not the emissions produced once the hydrocarbons are consumed. In Appendix E I provide an example of the role of two-sided vertical heterogeneity in determining the within-location equilibrium response to across-location entry and exit of capital.

Equilibrium is defined as a set of prices $p_{l,x,y}$, matching probabilities $q_{l,y}^{project}$ and $q_{l,y}^{capital}$, and a

[22]See, e.g. `https://www.eia.gov/energyexplained/natural-gas/natural-gas-and-the-environment.php`.

spatial capital distribution $\{n_{l,y}\}_{l\in L, y\in\{low,mid,high\}}$, that satisfies:

1. 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) - (2) and the queuing model detailed in Appendix C.2.

2. 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 (3) - (5).

3. Prices $p_{l,x,y}$ determined by Nash bargaining, defined in Equations (6) and (7).

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

5 Estimating the model

5.1 Overview

I provide an overview of the parametric assumptions used, and whether the parameters are estimated or calibrated, in Table 3.

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 $t_{backlog} = 6$ months, which is around the 75th percentile of backlog in the deepwater US market.[23]

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

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

Table 3: Overview of how the parameters are computed

Object	Notation	Parameterization	Param.	Method
Calibrated params.	β, τ, t_{max}			Calibrated
	η, P_{exit}, c_d			
Costs	$c_{l,y}$	$c_{l,y} = \gamma \bar{p}_{l,y}$	γ	Estimate step 1
Remain in loc.	b_{stay}		b_{stay}	Estimate step 1
Preference shock	σ_ε	Logit	σ_ε	Estimate step 1
Demand distribution	$f^{entry}_{l,x}$	Log-normal	μ_l, σ_l	Estimate step 2
Demand draws	D_l	Poisson dist.	λ_l	Estimate step 2
Match value	$m_{x,y}$	$m_{0,y} + m_{1,y}x$	$m_{0,y}, m_{1,y}$	Estimate step 2

cost of towing as $c_d = \$0.25$ million.[24]

I need to calibrate the bargaining parameter and I assume that the parties split the match surplus equally and set this to $\eta = 0.5$.[25] 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. I choose a value of $P_{exit} = 0.5$.[26]

Discussion of parametric assumptions I assume that the distribution of complexity for new wells $f^{entry}_{l,x}$ is given by a log-normal distribution with mean μ_l and standard deviation σ_l.

Estimating a separate cost for each capital type in each location would require estimating 18 different costs. However, given there are several markets where the number of relocations for a given capital type are small, I choose to parameterize costs in the following way: $c_{l,y} = \gamma \bar{p}_{l,y}$. Here $\gamma \in [0,1]$ is a scale parameter that relates costs to the average price in each location. Note that $1-\gamma$ is the capital's markup and so a low γ corresponds to a high markup and a high γ corresponds to a low markup.

[24] 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, Hellingaand and Leerdam (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.

[25] This is somewhat close to the $\delta = 0.37$ used in the shallow water analysis in Vreugdenhil (2023).

[26] Brancaccio, Kalouptsidi and Papageorgiou (2020) also need to calibrate a similar value for their 'exporter survival rate'.

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 complementarities between applying a type-y rig to a type-x well. I further discuss these complementarities in the estimation results (Section 6).

I now discuss the two estimation steps in more detail. I only use data in estimation in the period outside the US 2010 drilling moratorium.

5.2 Step 1: Computing supply side parameters

This section is similar in spirit to the estimation strategy in Brancaccio, Kalouptsidi and Papageorgiou (2020) except that I depart from it to allow for unobserved cost shocks. To do so I split estimation into two sub-steps. In Substep 1.1 I recover $\delta_{l,y}$, σ_ε, and b_{stay} using the observed choice probabilities of moving between locations. In Substep 1.2 I use an instrumental variables strategy to compute the markup γ — which can be used to back out $c_{l,y}$ — in the presence of unobserved cost shocks which may generate price endogeneity.

Substep 1.1: I estimate the parameters in this substep by fitting the empirical location choice probabilities for each rig type 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 provide a more formal proof of identification in Appendix D.1.

Overall, the identification intuition is that b_{stay} is identified by the probability of an available rig remaining in the same location. The $\delta_{l,y}$ parameters are identified by matching the probability of a single location choice per location (e.g. the choice probability of a move from the Asia to Africa for high-specification rigs would identify $\delta_{Asia,high}$). In one location (the US market) I have information on deepwater rig operational expenses from Kaiser and Snyder (2013), and so I incorporate this information into estimation by calibrating $\delta_{US,y}$ based on this.

Finally, given the other parameters, there are many remaining location choice probabilities to pin down σ_ε. Intuitively, the model matches these choices 'on average', with higher σ_ε corresponding to choice probabilities that generate a more 'spread out' stationary distribution of rigs in each location. Lower values of σ_ε yield location choices where rigs predominately choose locations with the highest markups (as well as the highest probability of matching).

Substep 1.2: Using the parameterization of costs in terms of a markup over the average price $c_{l,y} = \gamma \bar{p}_{l,y}$, I then use the values of $\delta_{l,y}$ from Substep 1.1 to estimate γ using the equation $\delta_{l,y} = (1-\gamma)\bar{p}_{l,y} + \xi_{l,y}$. Since prices may be endogeneous and a function of the unobserved cost shocks $\xi_{l,y}$ I use an instrumental variables strategy.

Specifically, I instrument prices with a demand shifter: unexploited oil and gas reserves by location and water depth.[27] The intuition for why this instrument is independent of the rig cost shocks ξ_{jt} stems from industry norms around the contractual division of responsibility between oil companies and rig owners detailed in Section 2.[28]

As a result, even though the volume of hydrocarbons may be correlated with underlying geological conditions that make the well more costly to drill, this is *not* a cost that would affect ξ_{jt}. Rather, the cost shocks in ξ_{jt} may come from, for example, local labor market conditions that make workers more costly to hire; these are unlikely to be correlated with the geology of deepwater oil and gas fields. For similar reasons, this instrument also satisfies the exclusion restriction (i.e. does not directly enter the utility function of the rig): rig owners do not directly benefit from selling the hydrocarbons the well produces.

5.3 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

[27] I use data from the 'Global Oil and Gas Extraction Tracker' from the Global Energy Monitor: https://globalenergymonitor.org/projects/global-oil-gas-extraction-tracker/. Within each location, I convert gas reserves to 'barrels of oil equivalent'. I then split up the total reserves into three quantiles of water depth and compute the share of unexploited reserves below the maximum of each water depth quantile.

[28] Specifically, rig owners are responsible for rig operating expenses like wages for the crew; oil companies pay for well-related drilling expenses but own the hydrocarbons the well produces.

distribution of prices identifies the underlying distribution of well types. Therefore, I spilt Step 2 into two substeps: I first retrieve the parameters that underlie the match value function (as well as demand) in the US market using simulated method of moments. Then, I use the estimated match value parameters and data on prices and utilization to estimate the equilibrium distribution of potential projects in the other markets using simulated method of moments.

Moments and identification The six match value parameters ($\{m_{0,y}, m_{1,y}\}_{y \in \{low,mid,high\}}$) are determined by two sets of moments constructed using data from the US market. First, I include moments that match coefficients from the following auxiliary regression of prices on project complexity and capital type for each contract in the US market where project characteristics are observed:

$$\text{price}_i = \beta_{0,y} + \beta_1 \text{complexity}_i + \beta_2 \cdot (\text{max drilling depth})_i \cdot \text{complexity}_i + \varepsilon_i \tag{8}$$

where $\beta_{y,0}$ is a capital-specific fixed effect. Equation (8) captures the relationship between prices and contract characteristics through the match value in the Nash Bargaining solution. Intuitively — for a given match and after adjusting for the outside options of the parties — a higher price corresponds to a higher match value. I match three coefficients from this regression: $\beta_{low,0}, \beta_1, \beta_2$. Second, I include the average price for each capital type (3 moments). Intuitively, the average price moments identify $m_{0,y}$. Fitting the remaining three moments from the auxiliary regression identifies the $m_{1,y}$ parameters that govern complementarities between capital type and project type.

Once the match value parameters are pinned down, the parameters that characterize the distribution of project entry (μ_l, σ_l) are identified from the following moments. For the US market, these parameters are identified by moments related to the average well-complexity match for each capital type (3 moments). These moments also ensure that the model matches the sorting patterns between capital and projects. For the non-US market these parameters are identified by matching the average prices for low and high capital types (2 moments per market). Finally, the Poisson parameter for new project entry λ_l is determined by the average capital utilization in each market (1 moment per market); higher values of λ_l correspond to higher capital utilization.

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 with the weight matrix as the identity matrix, except for the average well-complexity match moments which I weight by 0.1 to ensure they are of the same scale as the other moments.

6 Results

Supply side parameters Table 4 presents the estimated parameters from both the supply side and the demand side. Values for costs, match value parameters, and the other parameters, are given in millions of dollars per day. The values for the preference shock σ_ε and the stay put benefit b_{stay} in Table 4(c) are both relatively low. For example, scaling up the σ_ε to a per-month value (i.e. the value per period in the model) is \$4.2 million; the total price paid to a rig on average per match (with a six-month contract) is \$54.4 million.

The 'unexploited oil reserves' instrument used in the second substep to estimate γ is a strong instrument, with a first-stage F-statistic of 113. In Table 4(a) I report the average cost over all rig types within a location; I report costs also broken out by rig type and location in Online Appendix Table A-2. Overall the estimates reveal heterogeneity in rig operational costs across regions. For example, Europe has some of the highest drilling costs globally, consistent with this region having higher employment standards and salary requirements for workers which is a major component of rig owner operational expenses.

Demand side and match value parameters The fit of the model to the targeted moments is detailed in Appendix Table A-1; since the model is exactly identified the model closely fits the empirical moments. I also perform a model validation exercise centered around predicting the average prices of mid-specification rigs in each location. These moments are not used in

Table 4: Estimation results

(a) Location-specific Parameters

	Costs (av. over y) $c_{l,y} = \gamma \bar{p}_{l,y}$	# Entry λ_l	Mean μ_l	Std. dev σ_l
Africa	0.20†	6.33	0.59	1.06
	(0.0015)	(0.23)	(0.15)	(0.20)
Asia	0.17†	5.62	0.58	0.89
	(0.0013)	(0.26)	(0.13)	(0.15)
Australia	0.19†	2.97	0.60	0.70
	(0.0014)	(0.36)	(0.18	(0.20)
Central Am.	0.21†	3.58	0.82	0.85
	(0.0016)	(0.47)	(0.18)	(0.28)
Europe	0.21†	14.38	0.56	0.96
	(0.0016)	(1.28)	(0.17)	(0.24)
Mid East	0.17†	3.09	0.62	0.71
	(0.0013)	(0.55)	(0.29)	(0.26)
South Am.	0.15†	10.93	0.66	0.84
	(0.0011)	(0.65)	(0.10)	(0.15)
US	0.17†	6.68	0.78	0.79
	(0.0013)	(0.26)	(0.06)	(0.05)

(b) Match value parameters

	$m_{0,y}$	$m_{1,y}$
Low-spec	0.579	-0.324
	(0.039)	(0.040)
Mid-spec	0.329	-0.0100
	(0.047)	(0.018)
High-spec	0.343	0.028
	(0.036)	(0.012)

(c) Other parameters

Scale parameter (γ)	0.465
	(0.004)
Preference shock (σ_ε)	0.14
	(0.02)
Stay put benefit (b_{stay})	0.10
	(0.03)

Note: Standard errors in brackets computed using 200 bootstrap replications. The † symbol on the cost estimates indicates that reported here is the average of the costs over the rig types in each location. The full cost matrix — which is used in the counterfactuals — is reported in the Online Appendix.

estimation (with the exception of the US market). I plot the fit to these untargeted moments in Appendix Figure A-3. The model also closely fits the untargeted moments with a median difference of only 6.1 percent.

The demand parameter results are in the second, third, and fourth columns of Table 4(a). 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 $m_{0,y}$ and $m_{1,y}$ in Table 4(b). 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 it may be positive (more complex projects tend to produce more oil). Overall, the match value estimates indicate that low-specification rigs have an advantage in drilling simple projects. Conversely, high-specification rigs have an advantage in drilling more complex wells.

7 Counterfactuals

I investigate counterfactual scenarios that centre around two policies: a moratorium on drilling complex wells and a moratorium on drilling simpler wells. These policies correspond to real-world potential regulations in the industry. In terms of a moratorium on drilling complex wells, this is reflected in the practical effects of a ban on new drilling permits or new leases, as has been proposed but not fully implemented by the Biden Administration: Friedman (2023).

Specifically, over time the industry has expanded into deeper waters (which are more complex to drill, involving higher pressure formations and greater depths), and so new permits and lease sales tend towards these kinds of wells.[29] In terms of a moratorium on drilling simpler wells, this is an extreme case of the current policy emphasis in the United States which favors ultra-deepwater drilling and drilling complex wells through subsidies (for example, 'royalty relief' for deep fields (US Code Title 43)). In the case where regulators were trying to limit drilling through a partial ban, the regulator might therefore reflect the current bias and allow for ultra-deepwater drilling while banning other well types.

I evaluate the efficiency of these policies if they were implemented using incomplete versus more complete regulation. I begin with US-only regulation, motivated by the fact that many proposed policies for the domestic US industry are not developed cooperatively with other regions. I then consider a more coordinated increase in standards through a coalition of 'richer countries' (incorporating the US, Europe, Australia, and South America). 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). Finally, I consider a global agreement.

The counterfactual results are reported in terms of percentage changes. The benefit (discussed further in Appendix A) is that converting from deepwater market production to emissions essentially involves scaling by a multiplicative factor. Percentage changes are scale-free and therefore robust to the choice of this multiplicative factor.

Computation Unlike in estimation, where I was able to leverage empirical objects like the probability of matching and prices to simplify the computation, in the counterfactuals I need to re-solve for the entire equilibrium. I provide the algorithm in Appendix C.3.

[29] Recall that in order to drill a well, a tract on the ocean floor needs to be leased from the government and then a permit to drill needs to be granted. This system is typically used throughout the world. A lease and permit grant an oil and gas company the option to drill a well. Gramling and Freudenburg (2012) provide a summary of the evolution of the industry in the US.

Decomposition of capital misallocation I decompose capital misallocation from regulation into three effects.[30] The first is a quantity effect: fixing the sorting patterns across the world (that is, the quality of the match across locations) the ban corresponds to fewer wells available to match.

As a response, capital reallocates to avoid this direct effect by moving to other regions of the world where the probability of matching is higher, or to other types of wells that are not banned in the same location. This generates a second and third source of capital misallocation. The second source is that there may be misallocation due to spatial heterogeneity: for example, the operational expenses (the $c_{l,y}$ terms) may be higher in the markets that capital moves to. That is, I assume that rigs and wells are homogeneous and measure the change in match quality here comparing the average match $m_{x,y}$ net average drilling costs $c_{l,y}$ across locations. The third component is lower match quality that arises after accounting for two-sided vertical heterogeneity. To decompose this effect on quality, I allow for rigs and wells to be heterogeneous, which accounts for the remaining change in profits. Amongst other things, this allows the sorting patterns across locations to adjust in reaction to the policy.

Role of two-sided vertical heterogeneity The counterfactuals revolve around truncating the distribution of wells (demand). This leads to heterogeneous direct effects on the rigs that sort towards these kinds of projects. For example, a ban on complex wells disproportionally affects high-specification rigs who usually sort towards these projects, causing two effects. First, these rigs to leave for unregulated locations with many complex wells. Second, these rigs can re-match with simpler projects in their current location. This generates rich indirect effects in equilibrium, with other rig types indirectly affected as high-specification rigs displace projects they usually sort towards within a location. This then spurs additional equilibrium exit of other rig types.

There are two themes to the policy implications which arise from the behavior described above. First, coordinated regulation will be more effective if it can account for match

[30] Note that because the regulation does not affect drilling costs the entire decrease in profits can be interpreted as occurring due to misallocation compared to the status-quo baseline.

complementarities. For instance, if a ban on complex wells does not cover all locations where high-specification rigs are well-matched, then this could result in a high degree of leakage. Second, accounting for two-sided vertical heterogeneity affects the quantitative predictions of the model. For example, if high-specification rigs enter a location, they relax capacity constraints on complex wells, resulting in more oil produced and resultant emissions compared to an 'average' well. In addition, as mentioned, there is an additional source of capital misallocation compared to when agents are homogeneous: mismatch in match quality.

7.1 Discussion: Ban on complex wells

I implement the ban on drilling complex wells by eliminating wells with a complexity index greater than 4.0, which is around the upper third of well complexity globally. The results are in Figure 5.

US-only ban I first consider the effect of a ban on complex wells only in the US market. The results in Figure 5(a) show that the regulations decrease carbon dioxide emissions by reducing oil production in the US by -47.0% but also reduce profits by -30.8%.

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)) and did not allow for the possibility of capital reallocation, they might conclude that the regulation is effective in reducing pollution, albeit expensive. However, looking at the total effect reveals that the regulation is -78.1 percent less effective — as measured by the reduction in total emissions — due to capital reallocation.

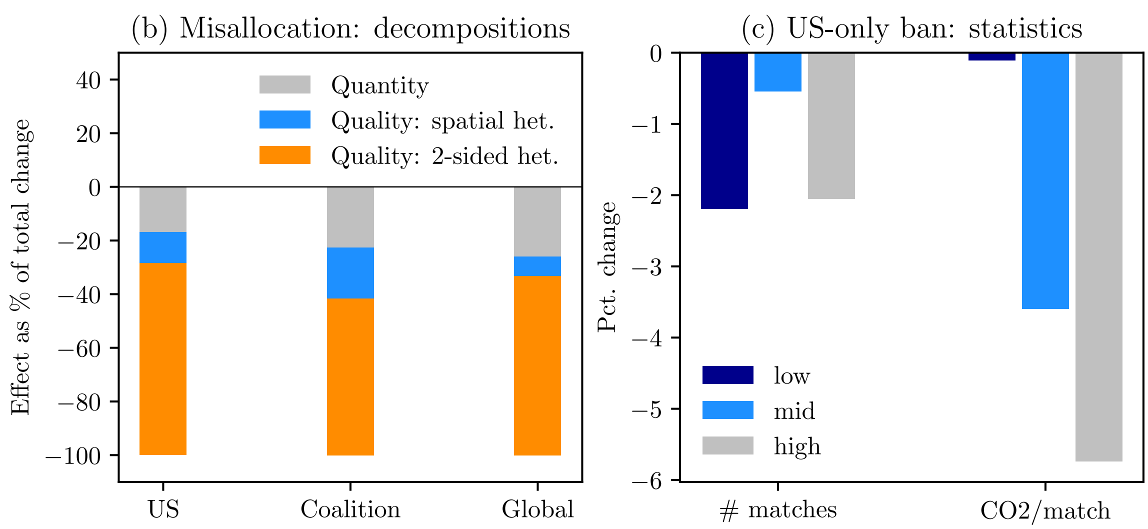
The leakage analysis in Figure 5(a) shows where this inefficiency is coming from. Re-sorting of rigs to other matches within the US implies that for every unit of carbon dioxide saved due to the regulation, 0.24 units are generated through increased drilling of other well types. Leakage across space is also important: for every unit of carbon dioxide saved by decreasing production in the US, 0.19 units are produced elsewhere. Leakage in profits is of a similar magnitude.

Figure 5(b) decomposes how the ban generates misallocation; the component that arises

Figure 5: Counterfactual: complex well ban

(a) Overall results

Counterfactual	Leakage (per unit)		Total changes (percent)		
	Re-sorting within regulated locations	Spatial	Regulated locations	Global	Δ Total from reallocation
US-only ban					
CO_2	0.24	0.19	-47.0	-6.9	-43.2
Profits	0.32	0.15	-30.8	-4.7	-46.7
Coalition ban					
CO_2	0.14	0.20	-45.3	-21.5	-33.7
Profits	0.01	0.28	-25.2	-11.9	-28.5
Global ban					
CO_2	0.28	0.00	-43.6	-43.6	-28.2
Profits	0.41	0.00	-22.6	-22.6	-40.9



Note: Part (a): Leakage is defined as the increase in emissions (or profits) generated through unregulated economic activity, for a one unit decrease in emissions (or profits) in the regulated activity. I decompose this into leakage due to capital reallocation from re-sorting within regulated locations, and leakage from the movements of capital to other locations. The column 'Δ Total from reallocation' is the total decrease in effectiveness compared to a 'no reallocation benchmark' where sorting patterns and rig locations are fixed. Part (b): see text for a description. Part (c): Appendix A-4 has detail on this figure for the other counterfactuals.

from two-sided vertical heterogeneity is responsible for the majority of misallocation. Figure 5(c) illustrates some key statistics that underlie the results. All rigs are matched with a lower probability. However, mid-specification rigs are the least affected; these rigs have more matching complementarities with other markets than low-specification rigs, and so can relocate. As well, these rigs find it more profitable to reallocate to simpler projects within the US market compared to high-specification rigs.

This reallocation affects the sorting patterns, which affects which kinds of wells are drilled, which then affects carbon emissions. As illustrated by the results in the carbon dioxide per match in Figure 5(c), a ban on complex wells causes high and mid-specification rigs to reallocate towards simpler wells. Although the rigs are less well-matched here, there is an environmental benefit: these wells tend to produce less oil and therefore less emissions once the oil is burned.

Coalition ban The 're-sorting within location' leakage figures in Figure 5(a) for emissions are lower for coordinated regulation than for US-only regulation. But, these figures are around the same for leakage across space in emissions. The reason that spatial leakage is relatively similar is that although more regions are under regulation, the coalition does not encompass all locations with complex wells. Since a ban on complex wells disproportionally affects the matching of high-specification rigs, these rigs are left with alternative unregulated locations to where they can escape the regulation and still be well-matched, like Africa. Put another way, it is not enough to reduce leakage to just add more regulated areas; these regulated areas need to account for match complementaritites and sorting patterns.

Overall, capital reallocation undercuts the efficacy of the regulation in terms of total global emissions by -33.7 percent.

Global ban Finally, I consider how a coordinated global agreement would affect the market. Since regulation is now uniform, there are no unregulated locations. However, there are still well types which are not banned within each location. As a consequence, although there is no leakage across space, shutting down this channel exacerbates leakage within-location to 0.28 tons of carbon dioxide produced elsewhere for every ton saved directly from the ban.

Globally, the change in emissions is -43.6 percent, and is greater than under the coalition counterfactual. This is mainly coming from more locations under regulation. Reallocation still lowers the efficacy of the regulation substantially at -28.2 percent.

7.2 Discussion: Ban on simple wells

I implement the ban on drilling complex wells by eliminating wells with a complexity index less than 2.0, which is around the lower third of well complexity globally. The results are in Figure 6.

US-only ban A striking feature of the US-only ban on simple wells is that capital reallocation undercuts the efficacy of the regulation even more than in the complex well ban case, at -78.1 percent. This is repeated throughout the counterfactuals in Figure 6(a); in fact, in the coalition ban and the global ban emissions actually increase.

Focusing in on the US-only case, spatial leakage is predominately responsible for this reduction in effectiveness, at 0.54 tons of carbon dioxide produced in other locations for every ton saved in the US market. Why is leakage so high in this counterfactual? Note that a ban on simple wells disproportionally reduces the probability of a low-specification rig matching, who sort towards these kinds of projects. This has two consequences. First, low-specification rigs leave for other locations, which relaxes capacity constraints in these locations (in the context of the model, the probability that a rig's queue is full is reduced) and so increase the number of matches elsewhere.[31]

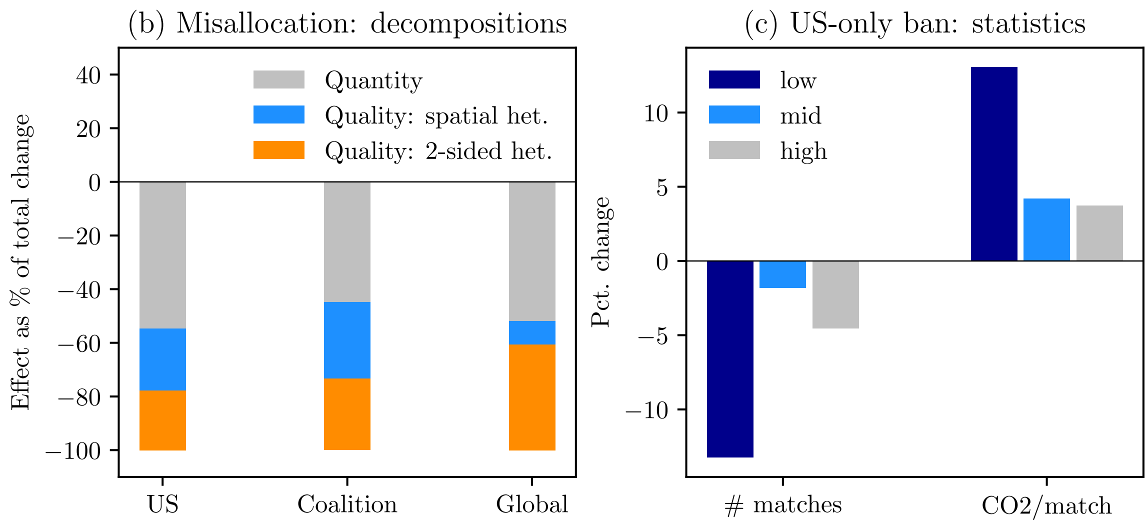
The second consequence is that the ban causes complex wells to re-target matching towards low-specification rigs within each regulated location. This re-targeting occurs because the probability of matching with a low-specification rig is now higher. Overall, this moderates the carbon pollution benefits of the ban within the US market, as is apparent in the carbon dioxide per match results in Figure 6(c).

[31] According to the estimated framework, these new locations do *not* contain matches that are substantially lower quality. In fact, looking at Figure 6(b) the quality effect corresponding to two-sided vertical heterogeneity is quite small. However, these regions contain fewer potential matches — and so the rig is more likely to be unemployed — and also may have higher rig operating costs.

Figure 6: Counterfactual: simple well ban

(a) Overall results

Counterfactual	Leakage (per unit)		Total changes (percent)		
	Re-sorting within regulated locations	Spatial	Regulated locations	Global	Δ Total from reallocation
US-only ban					
CO_2	0.25	0.54	-21.0	-1.2	-78.1
Profits	0.02	0.30	-37.9	-5.2	-31.1
Coalition ban					
CO_2	1.53	0.00	16.0	9.9	-153.2
Profits	0.40	0.01	-28.0	-18.0	-41.3
Global ban					
CO_2	1.17	0.00	7.3	7.3	-116.9
Profits	0.43	0.00	-33.4	-33.4	-43.2



Note: Part (a): Leakage is defined as the increase in emissions (or profits) generated through unregulated economic activity, for a one unit decrease in emissions (or profits) in the regulated activity. I decompose this into leakage due to capital reallocation from re-sorting within regulated locations, and leakage from the movements of capital to other locations. The column 'Δ Total from reallocation' is the total decrease in effectiveness compared to a 'no reallocation benchmark' where sorting patterns and rig locations are fixed. Part (b): see text for a description. Part (c): Appendix A-4 has detail on this figure for the other counterfactuals.

Coalition ban Given that leakage from capital reallocation undermines the US-only ban, one might ask whether more coordinated regulation would improve the results. The 'coalition of rich countries' example in Figure 6(a) shows that this would indeed eliminate spatial leakage. This is because the locations in the coalition encompass most of the global demand for simple well drilling.

However, with no alternative locations to move to, low-specification rigs — which usually match with simple wells — instead reallocate to more complex wells. These wells generate more oil and therefore more emissions once the oil in consumed. This generates a leakage number greater than 1. As a result, emissions actually increase from the ban.

Global ban A global ban also eliminates spatial leakage and overall does better than the coalition ban in terms of the overall changes in pollution. However, the within-location capital reallocation effect is still present here, and global emissions still rise compared to no regulation.

8 Conclusion

Incomplete regulations are ubiquitous. In this paper I develop a framework to shed light on how incomplete regulation operates through the capital reallocation channel in a decentralized factor market. The model extends the literature on spatial matching models in industrial organization to incorporate two-sided vertical heterogeneity of firms leading to sorting. 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 supply-side climate policies, when implemented through incomplete regulation, induce large responses through capital reallocation. This reallocation undercuts the environmental benefits of regulation, causing oil to be produced elsewhere in the world while inducing spatial misallocation. A coalition of rich countries implementing coordinated regulation — while politically feasible — may not be effective if it fails to account for match complementarities. For some regulatory designs these agreements may even result in an increase in global emissions. Overall, the results illustrate that capital reallocation is a primary concern for leakage and should be a central consideration in policy design.

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