

# Booms, Busts, and Mismatch in Capital Markets: Evidence from the Offshore Oil and Gas Industry

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How efficiently do markets reallocate capital in booms and busts? Using a novel dataset of offshore drilling contracts, I examine the role of matching in shaping industry reallocation. Oil companies search and match with capital (rigs) in a decentralized market. I find that oil and gas booms increase the option value of searching, which leads agents to avoid bad matches, reducing mismatch through a sorting effect. I provide an identification strategy to disentangle unobserved demand changes from the sorting effect. Estimating a model, I find substantial benefits to the sorting effect and an intermediary, but I find that demand-smoothing policies are ineffective.

## I. Introduction

When markets surge in a boom or crash in a bust, firms adjust by reallocating capital. Although it is well established that fluctuations, reallocation, and movements in aggregate productivity are broadly linked, the exact

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process of capital reallocation within industries is not well understood.<sup>1</sup> Filling this gap is important because the costs and benefits of often-proposed policies—such as demand smoothing—hinge on the reallocation mechanism.

In this paper I focus on markets where output is made by matching heterogeneous producers and heterogeneous factor inputs. Here, booms increase entry rates, which can create thick factor markets. This increases the probability of matching, which gives the parties a greater option value of searching for a better match. In booms, so long as the value of a match does not increase too much and there is some persistence in the cycle, agents become more selective and avoid bad matches. This results in a sorting effect, where agents are more assortatively matched; these better matches and complementarities in booms reduce factor misallocation and create procyclical productivity movements.

Overall, the goal of this paper is to answer the following questions: what is the quantitative importance of the sorting effect, and to what extent does it spur efficient capital reallocation in booms and busts? I answer these questions in the context of the market for offshore oil and gas drilling rigs—an outstanding example of a cyclical decentralized capital market. Using a novel dataset of contracts and projects, I show that booms (caused by increases in oil and gas prices) are associated with matching consistent with the sorting effect. I then develop a framework to quantify the efficiency of reallocation in a decentralized capital market with two-sided vertical heterogeneity that combines elements of the search and matching literature and the firm dynamics literature. Applying the framework to the data, I illustrate the economic significance of the sorting effect and quantify the value of an intermediary and a demand-smoothing policy.

It is important to note that the fact that booms are associated with a sorting effect is not mechanical. Rather, it is an empirical question whether stronger sorting is optimal in booms. This is because the value of a match also increases in booms (since oil companies receive a higher price for a given quantity of oil and gas), and therefore it may be optimal to be less selective. Overall, I find that the option value effect dominates the match value effect in the data, leading to procyclical match quality.

The market for offshore drilling rigs is an excellent setting for studying booms and busts because it is subject to large exogenous fluctuations in drilling activity caused by global oil and gas prices. Oil and gas companies

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<sup>1</sup> This is largely due to the lack of producer-level data on covariates, e.g., contracts, production, and relationships; Collard-Wexler and De Loecker (2015) make a similar argument to motivate their study on reallocation in the US steel sector. For a broader review of the literature, see Eisfeldt and Shi (2018).

undertake projects (wells) but do not own capital (drilling rigs). Instead, they must search for capital in a decentralized market. Capital can be ranked using an industry measure of efficiency, and projects can be ranked using an engineering measure of complexity. The quality of the match matters: more efficient capital is suited to drilling more complex projects, and this is reflected in sorting patterns in the industry. Therefore, in the offshore drilling industry, stronger sorting corresponds to more efficient rigs matched to more complex wells and less efficient rigs to simpler wells, as illustrated in figure 1.

I focus on shallow-water oil and gas drilling in the US Gulf of Mexico in 2000–2009. I begin by discussing several features that suggest that search frictions, such as the existence of brokers and the emergence of e-procurement, are important in this industry. I then document two main findings. First, there is positive assortative matching: more efficient drilling rigs tend to drill more complex wells. Second, booms are associated with matching patterns consistent with stronger sorting. In a bust (when oil and gas prices are low), all rigs drill relatively similar types of wells. In a boom, high-efficiency rigs tend to match to more complex wells and low-efficiency rigs tend to match to simpler wells.

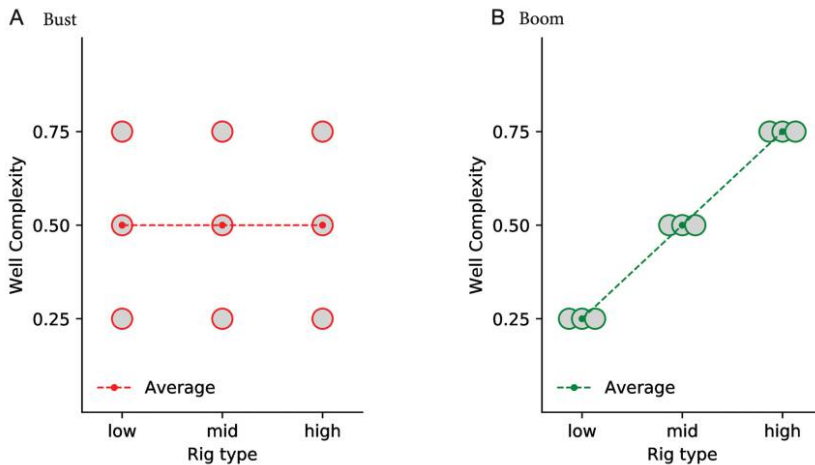


FIG. 1.—Illustration of the sorting effect. Suppose that in both panels there are three rigs of each type, {low, mid, high}, and three wells of each type, {0.25, 0.5, 0.75}, where a higher number corresponds to a more complex well. Each panel plots an allocation of the nine wells to the nine rigs. In a bust, all rigs drill similar wells, resulting in a flat average match line. In a boom, simple wells are allocated to low-efficiency rigs, and complex wells are allocated to high-efficiency rigs, resulting in a more diagonal average match line. For a fixed number of rigs and wells, as long as the match value is supermodular in rig type, there will be higher total output in the boom allocation.

Next I estimate a model that captures the institutional details of the industry as well as the economic logic behind the sorting effect. In the model there are searching agents on both sides of the market. On one side of the market there are projects (wells that need to be drilled that are owned by oil and gas companies). On the other side of the market there are drilling rigs (capital), which are differentiated by efficiency. The model is dynamic. In booms, more projects enter, increasing the market thickness and raising the option value of continuing to search for a better match. This also increases the opportunity cost of being locked in to a bad match. Agents respond by avoiding bad matches in two ways: they can reject bad matches, or, using the search technology, they can direct their search away from bad matches. Overall, these two channels result in stronger sorting patterns and reduce mismatch.

I estimate the model in two steps. I first construct value functions based on empirical objects in the data. Then I estimate parameters using the simulated method of moments. I use the estimated model to conduct three counterfactuals, and I measure welfare in terms of total profits.

The first two counterfactuals center around measuring the efficiency of capital reallocation in the market: quantifying the sorting effect and then assessing how much inefficiency remains after accounting for the sorting effect. I begin by starting from a “no-sorting” world, where rigs accept all matches and do not direct their search away from bad matches. Allowing for the sorting effect increases welfare by 12.0%, or around \$536 million, over the 2000–2009 period. The sorting effect is cyclical, with more efficiency gains in the boom. Decomposing the total effect highlights the main trade-off in the model: compared with the no-sorting-effect model, agents in the market tend to drill fewer wells, but this is outweighed by the fact that matches are higher quality.

Next, I quantify the benefits of an intermediary who can reduce search frictions by offering an improvement in the search technology. In addition to highlighting the effects of search frictions that remain even after accounting for the sorting effect, this counterfactual suggests potential gains from recent advances in e-procurement in the industry. Indeed, the potential of the internet to reduce search frictions in the industry has been discussed by practitioners since as early as 2002 (see Rothgerber 2002). I find that the intermediary would achieve a welfare gain of 51.0% compared to the market benchmark.

Finally, I consider a demand-smoothing policy, which would eliminate price cycles. This kind of intervention has precedent in the oil and gas industry: many producer incentives, such as tax credits and royalty rates, are tied to oil and gas prices. I find that demand smoothing would cause large shifts in drilling activity from booms to busts. However, the policy would increase overall welfare by only 14.9%, suggesting that such policies are somewhat ineffective.

Overall, this paper makes three main contributions. The first contribution is a novel dataset of a decentralized capital market that is subject to booms and busts. A major difficulty in studying firm-to-firm markets is that contracts are typically confidential. By contrast, in this paper I construct a dataset of the universe of contracts in the industry matched with rich microdata from the regulator on the characteristics of projects undertaken under these contracts. My analysis of the dataset presents a detailed picture of how firms make decisions when faced with fluctuations.

The second contribution is to solve a data limitation that often occurs in capital markets: demand (the distribution of searching wells) is not observed. To fully assess mismatch, I need to identify this object. For example, if only simple projects enter in a bust, then it would be optimal to assign high-efficiency capital only to simple projects. Hence, the potential benefits to an intermediary or demand smoothing would be low since there is less mismatch. Therefore, I provide an identification strategy to disentangle changes in the composition of searching projects from the sorting effect. I also show how a more flexible search technology—which nests typical assumptions of random search or directed search as special cases—can be identified from data on matches.<sup>2</sup>

Third, previous work typically uses a steady-state analysis to tractably incorporate two-sided heterogeneity in a search model.<sup>3</sup> When there are fluctuations, however, the distributions of agents change through time. In this paper I use an estimation strategy that incorporates—for the first time in a random search model with fluctuations—two-sided heterogeneity, distributions of searching agents that change over time, and Nash bargaining. The estimation strategy relies on the observation that the value of searching can be written in terms of data on contract prices and the probability of matching. My strategy is an extension of approaches in the industrial organization firm dynamics literature (e.g., Kalouptsi 2014) to cases where short-term contract data are available.

*Related literature.*—This paper is related to five strands of literature. First, it is related to the literature on capital reallocation. Eisefeldt and Shi (2018) provide a review of this literature. Recent work (e.g., Lanteri 2018) has tried to uncover the mechanisms by which markets reallocate capital. Several papers show that calibrated models incorporating search frictions can help to fit economy-wide facts about capital utilization and productivity (e.g., Ottonello 2018; Dong, Wang, and Wen 2020). This paper advances this literature by—for the first time—providing empirical

<sup>2</sup> Lentz and Moen (2017) consider a related setup. My approach differs because I need to deal with two-sided heterogeneity and fluctuations, which pose challenges for identification and estimation.

<sup>3</sup> An exception is Lise and Robin (2017), which models nonstationary distributions of searching agents by assuming Bertrand wage competition.

evidence of how search frictions affect the inner workings of a real-world capital market in booms and busts.

Second, this paper is related to the literature in industrial organization that studies empirical firm dynamics in decentralized markets. Some recent papers incorporate fluctuations into search models with homogeneous agents (e.g., Frechette, Lizzeri, and Salz 2019; Buchholz 2022). A related set of papers study how fluctuations affect long-run firm entry and exit decisions (Collard-Wexler 2013; Kalouptsidi 2014). Other recent papers estimate search and matching models with two-sided heterogeneity in a stationary context (e.g., Gavazza 2016). By contrast, my paper contains both fluctuations and heterogeneous agents, and I study how the two interact in a decentralized firm-to-firm market.

Third, this paper is related to the literature about the effects of the business cycle on labor search and matching. Many of these papers aim to rationalize empirical procyclical productivity patterns in labor markets, for example, through cyclical job ladders (Moscarini and Postel-Vinay 2018) or alternative mechanisms (Lise and Robin 2017; Barlevy 2002). My paper illustrates the relevance of search and matching models in explaining procyclical productivity patterns outside the standard labor market context.

Fourth, this paper is related to the theoretical literature on dynamic matching (e.g., Baccara, Lee, and Yariv 2020). Although my framework is quite different from that of Baccara, Lee, and Yariv, it shares a focus on quantifying the gains to a centralized intermediary.

Finally, this paper is related to the economics literature about the oil and gas industry. When modeling the industry, I build on some of the institutional features discussed by Corts and Singh (2004), Corts (2008), and Kellogg (2011, 2014). For credible estimation, my empirical strategy relies on having a measure of participants' expected value of undertaking a project. In the context of the Gulf of Mexico, an excellent proxy is available: participants' beliefs about the value of drilling a well are related directly to lease bids (Porter 1995).

## II. Industry Description and Data

### A. *Overview of the Offshore Drilling Industry*

Offshore drilling is an important part of the global oil and gas industry and was valued at \$43 billion in 2010 (Kaiser and Snyder 2013). I analyze a particular segment of this industry: shallow-water (<500-foot) drilling in the US Gulf of Mexico.

The offshore drilling industry is decentralized. Lease holders, such as BP and Chevron, do not own the equipment used to drill their wells. In order to drill a well, a drilling rig must be procured from a rig owner. Both

sides of the industry are unconcentrated, with a Herfindahl–Hirschman index (HHI) of 1,239 for rig owners and one of 335 for well owners, where I calculate the HHI with the definition of *market share* as the proportion of total contracts. Given that the concentration of this industry does not seem high enough for individual firms to exert substantial market power, I model the decision problem as a single agent playing against industry aggregates.

*What is a drilling rig (capital)?*—Shallow wells are drilled using jack-up rigs. Jack-up rigs are barges fitted with long support legs that can be raised or lowered. In order to drill a well, a jack-up rig first moves to a well site. Upon arrival, the rig then extends (jacks down) its legs into the seabed for stability and commences drilling. The rig drills 24 hours a day until the well is completed. Once the well drilling is completed, the well is connected to an undersea pipe where the oil and gas flow back to a refinery on land. The rig then jacks up its legs, leaves the well site, and moves on to the next drilling job.

*What is a well (a project)?*—Oil and gas producers own leases, which are tracts of the seabed where they can drill a well to extract oil and gas. In this paper I use the terms *well* and *lease* interchangeably. Wells produce both oil and natural gas in different quantities. In the shallow water of the US Gulf of Mexico, wells tend to contain more natural gas, so I focus on changes in the price of gas as the driver of exogenous shocks in this industry.<sup>4</sup> Once a well has been drilled, an operator extracts oil and gas at maximum capacity for the lifetime of the well (Anderson, Kellogg, and Salant 2018) unless external factors such as hurricanes intervene.

## B. Data

*Overview.*—I construct a new and novel dataset by exploiting a number of rich proprietary datasets of firm-to-firm contracts matched with the characteristics of wells drilled under each contract. Descriptive statistics for the industry are shown in table 1. I focus on the subset of data for the years 2000–2009. The year 2000 is the earliest year for one of the contract datasets, so it is the earliest year for which I have a full picture of the industry. In 2010 the now-infamous Deepwater Horizon oil spill triggered a new and tighter regulatory environment. Therefore, I focus on the years before 2010.

*Contract data.*—The contract data come from two sources: IHS and Rigzone. The Rigzone dataset contains all offshore drilling contracts worldwide. The Rigzone dataset has detailed information about the status of rigs currently drilling and whether they are not drilling and if they

<sup>4</sup> Furthermore, in the sample period the oil price is correlated with the natural gas price. I show in app. E.2 (apps. A–E are available online) that simply tracking the natural gas price does not make any difference to the results.

TABLE 1  
SUMMARY STATISTICS FOR DATASET

Variable	Units	<i>N</i>	Mean	SD	10%	90%
Rig price: new contracts	Thousands of USD per day	1,733	62	35	27	111
Duration: new contracts	Days	1,733	65	76	27	120
Rig price: renegotiations	Thousands of USD per day	922	52	26	28	81
Duration: renegotiations	Days	922	68	59	29	126
Value	Millions of USD	2,655	8.8	25	.25	8
Complexity	Index	2,655	.87	.51	.34	1.46
Water depth	Feet	2,655	117	80	37	233
Monthly utilization	% rigs under contract	360	.76	.2	.49	1.0

NOTE.—Monthly utilization is for each of the three types of rig over 120 months.

are not drilling, about whether they are available or off the market (e.g., the rig has been scrapped). I use these data to compute how many rigs are available at a point in time in the US Gulf of Mexico. In total there are 101 rigs, on average, in my sample period in the Gulf of Mexico. The IHS contract dataset has slightly more detailed information on whether the contract is new or an extension, so I merge this dataset with the well data.

Contracts follow a simple form: rig owners are paid a fixed-price day rate for the length of the contract. Contracts can differ in their length, and I treat differences in the duration of contracts as one of the characteristics of a project. Contracts are also often extended, and this is typically to drill a new well. A small number (11.0%) of contracts are turnkey contracts, which means that the rig operator, rather than the well owner, is responsible for additional costs if there are cost overruns, such as a well blowout. Since the proportion of turnkey contracts in my sample is smaller than that of Corts and Singh (2004), who study the industry in an earlier period (July 1998–October 2000), I do not model the choice of contract form explicitly.

*Well data.*—The well data come from the Bureau of Safety and Environmental Enforcement. The well permit data contain detailed information about the characteristics of each well, including depth, location, mud weight, oil and gas produced, and so forth.

In addition, I have lease bid data, from which I can estimate participants' beliefs about the value of drilling a well, because they are related directly to lease bids (Porter 1995). To do this I take the highest bid for the corresponding lease.<sup>5</sup> In order to back out the quantity of hydrocarbons in the well, I then divide by the average gas price in the sample. My measure is a monotonic function of the expected oil and gas deposit size.

<sup>5</sup> This is motivated by the fact that offshore lease auctions are common value auctions, and as the number of bidders  $n \rightarrow \infty$ , the maximum bid converges to the expected value of oil and gas in the prospect. Although in practice the number of bidders is finite, see Haile, Hendricks, and Porter (2010) for evidence that ex post returns in shallow-water outer continental shelf auctions are not excessive.

*Measuring well heterogeneity.*—To rank wells I compute an engineering model of well complexity used in the industry, called the mechanical risk index. The mechanical risk index takes well covariates, including depth, mud weight, horizontal displacement, and so forth, that describe the geological environment and transforms them into a one-dimensional index of well complexity.<sup>6</sup> More complex wells (e.g., a deep well that needs to bend around a difficult geological formation) are more costly to drill because there is a higher probability of encountering a problematic formation. Costs are typically in the form of extra materials when the rig encounters a problem. A higher ranking on the index corresponds to a more complex well.

*Measuring rig heterogeneity.*—Rigs are vertically differentiated. A natural ranking for capital (drilling rigs) is their maximum drilling depth in water, which ranges from 85 to 450 feet. This is a good proxy for many other characteristics of rig efficiency, including age and technology. This ranking is also used in the industry, and rig owners market rigs that can drill in deeper water as high-specification rigs. Because of a limited sample size, for estimation I aggregate rigs into three classes by their maximum drilling depth: low-efficiency rigs ( $\leq 200$  feet), mid-efficiency rigs ( $> 200$  and  $< 300$  feet), and high-efficiency rigs ( $\geq 300$  feet). (Note that the split is not quite exact because there are sometimes many rigs of exactly the same drilling depth.) One might ask whether rigs are also differentiated by other factors. Two possible factors are (i) the distance between a rig and a particular well and (ii) past experience between a rig operator and a well owner. I provide a discussion in appendix A.3 about why it is likely that these factors are of probably of limited importance in the offshore oil and gas industry.

### C. Key Features of the Industry

My model focuses on three key features of the offshore drilling industry: (1) sorting patterns, (2) booms and busts driven by oil and gas prices, and (3) search frictions.

#### 1. Feature 1: Sorting Patterns

Figure 2 illustrates the pattern of positive assortative matching in the data. It shows that better rigs tend to drill more complex wells, on average. In addition, I plot the 10% and 90% quantile of well complexity observed in the sample. The figure shows that although there is positive sorting, there is not perfect segmentation in this industry: even the highest-ranked rigs still drill simple wells.

<sup>6</sup> Details on the calculation of the mechanical risk index can be found in app. A.2.

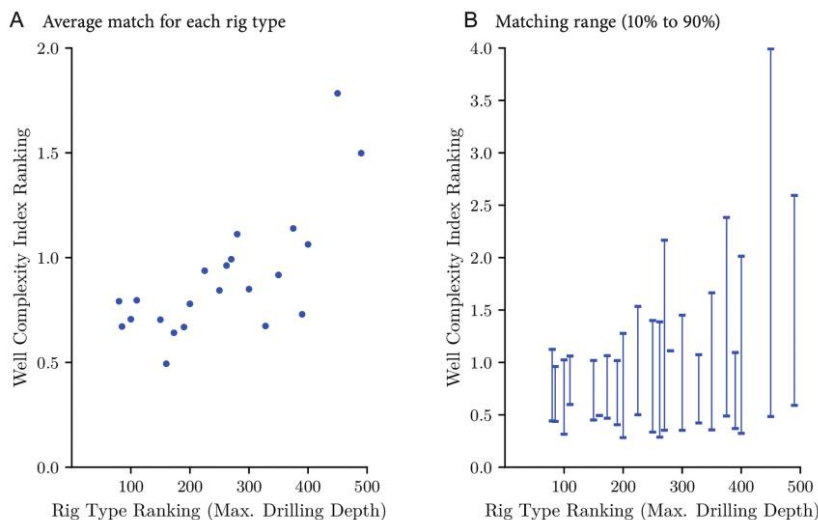


FIG. 2.—Positive assortative matching. Higher-ranked rigs match with more complex wells. Rigs are constructed in discrete increments of maximum drilling depth, so each point on the  $x$ -axis might correspond to many unique rigs.

The observed sorting patterns imply that the match between rig technology and well complexity matters. Qualitative evidence from the industry provides more detail about how agents make decisions about whom to match with. For example, the website of Diamond Offshore, a rig owner, states, “Oil companies (‘operators’) select rigs that are specifically suited for a particular job, because each rig and each well has its own specifications and the rig must be matched to the well.”<sup>7</sup> Note that in table A-1 (tables A-1–A-10 are in the online appendixes), I perform a hedonic regression of prices on match characteristics.

## 2. Feature 2: Booms and Busts

Figure 3 displays how fluctuations in natural gas price affect rig prices in the industry. Figure 3 shows that there is a strong correlation between gas prices and rig prices: rigs can command prices in excess of \$100,000 per day when gas prices are high, but this can fall to \$30,000 per day when gas prices are low. Rig utilization is also cyclical, and I document rig utilization patterns in table A-5.

*How booms and busts affect matching.*—Figure 4A provides evidence consistent with stronger sorting in booms than in busts. In the figure, I split

<sup>7</sup> <http://www.diamondoffshore.com/offshore-drilling-basics/offshore-rig-basics>.

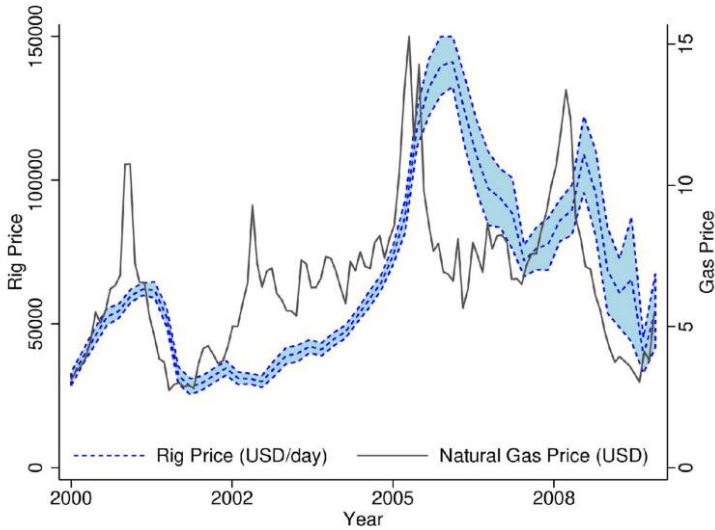


FIG. 3.—Booms and busts. How fluctuations in the natural gas price affect rig prices in the industry.

the data into two bins: a gas price above average, which I label a boom, and a gas price below average, which I label a bust. I then plot the average match in the raw data across the three types of rigs. Figure 4 shows a rotation in the average match line between rig rankings and well complexity rankings. Here, less efficient rigs are matched to simpler wells in booms than in busts, and more efficient rigs are more likely to be matched to complex wells in booms than in busts. I verify in figure 4B (which is based on confidence intervals from table A-4) that these effects are statistically significant across the boom-bust cycle and robust to controls for observables.

There are two possible explanations for the matching patterns in figure 4A. One explanation is stronger sorting: capital is better matched in booms. However, since the distribution of searching wells is not observed, these patterns may also arise from changes in the composition of searching wells (demand). Consistent with the stronger sorting explanation, in appendix D.3 I also show that there are stronger synergies between high-efficiency rigs and complex wells in booms, as reflected in prices.

### 3. Feature 3: Search Frictions

Rigs are selected in practice through the following process. Oil company engineers will first determine the well design, write up the details, and

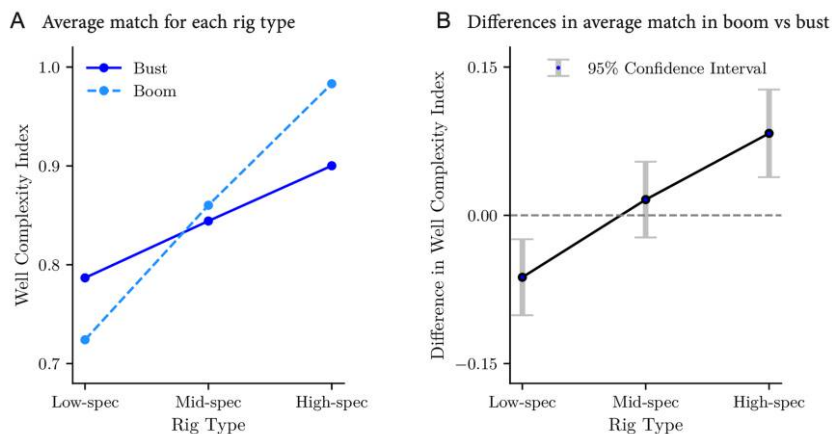


FIG. 4.—Matching patterns in booms and busts. *A*, When a bust turns to a boom, the market features stronger sorting patterns. *B*, Differences in matching patterns are statistically significant, using confidence intervals from table A-4. Figure A-3 (figs. A-1–A-6 are in the online appendixes) shows that the overall composition of matches in booms and busts is relatively similar.

initially solicit rigs, sometimes with the aid of specialized rig brokers. The rig selection process rarely ends there: offshore rig companies stress that the process of obtaining an offshore rig can be relatively unstructured, with further discussions between the parties, and that, ultimately, “our contracts to provide offshore drilling services are individually negotiated” (Transocean 2015, 7). Since my dataset contains only data on the eventual outcomes of this process and no information about interim discussions, I use a reduced form of how this process occurs in practice, ending with one rig ultimately selected.

Next, I discuss several institutional features that suggest search frictions in the industry. A key feature is that both rig owners and well owners often enlist the help of a fragmented group of brokers, such as Clarksons, Bassoe Offshore, and Pareto Offshore, to help find a match. As discussed by Brancaccio et al. (2023), the very existence of brokers has been used in a variety of settings as evidence of search frictions. In addition, another feature is the emergence of e-procurement in the industry.<sup>8</sup> These recent technological improvements to the search and matching process suggest that in the earlier period of this study, there were potential gains to better matching that were unrealized.

<sup>8</sup> For an early discussion about the potential benefits to e-procurement in the industry, see Rothgerber (2002). Raghthamarao (2016) discusses how advances in e-procurement are being used in the oil and gas industry.

Second, the industry is unconcentrated on both sides, with a large number of agents simultaneously trying to match with each other in an uncoordinated fashion. In addition, since this industry is constantly in flux, participants may not have good information about the status of other rigs.<sup>9</sup> As is argued in the macroeconomics search literature, modeling each of these sources of frictions and heterogeneity explicitly would “introduce intractable complexities” into the model (Petrongolo and Pissarides 2001, 390). Instead, I include a reduced-form matching function that allows for realistic frictions in the search process.

*Price dispersion.*—Next I show suggestive evidence for search frictions in the data by showing that different prices are paid for observationally equivalent matches. Although price dispersion is consistent with search frictions, note that it is not a sufficient condition, so the results in this section should be interpreted with that caveat. Since price will also vary with market conditions, I de-mean prices by the average price in each month. I regress these de-measured prices on rig characteristics, well characteristics, and contract characteristics. I run the following regression on new contracts:

$$\hat{p}_{it} = \mathbf{X}'\beta + \tilde{p}_{it}, \quad (1)$$

where  $\hat{p}_{it}$  is the de-measured price for match  $i$  at month  $t$  and  $\tilde{p}_{it}$  is the residual price (i.e., the residual after regressing prices on the covariates). I use the following covariate  $\mathbf{X}$ , which includes numerous fixed effects (FEs), as well as a third-order polynomial of the state variables (gas price and rig availability of each aggregated rig type) and interactions between rig types and a third-order polynomial of well characteristics and a third-order polynomial of contract duration:

$\mathbf{X} = \{$ well complexity, well water depth, well value, gas price,  
rig availability, contract duration rig type FEs, month FEs,  
year FEs, contractor FEs, rig owner FEs, rig to well distance $\}$ .

In table 2, I report the unexplained variation  $1 - R^2$ , the standard deviation of residual prices  $\tilde{p}_{it}$ , and the standard deviation of all prices  $\hat{p}_{it}$ . In column 1, rig type is the aggregated classes (i.e., using {high, mid, low}); in column 2, rig type is the disaggregated rig classes (i.e., by maximum drilling depth).

Despite controlling for detailed match and contract characteristics, table 2 illustrates that there is a high amount of unexplained price variation:

<sup>9</sup> For example, this includes information about which rigs have not yet signed a contract but are in a late stage of negotiations, or whether a rig suddenly needs maintenance, or some other idiosyncratic heterogeneity.

TABLE 2  
EVIDENCE OF PRICE DISPERSION

	Using Aggregated Rig Types (1)	Using Disaggregated Rig Types (2)
$1 - R^2$	.37	.27
$SD(\hat{p}_i)$	11	9
$SD(\hat{p}_i)$	18	18

NOTE.—Standard deviations are measured in thousands of US dollars per day. The dependent variable  $\hat{p}_i$  is prices de-meaned by the average price in each month. The residual from the price regression is denoted by  $\hat{p}_i$ .

a share of 0.37 of total price variation is unexplained when using the aggregated rig types, and a share of 0.27 of total price variation is unexplained when using the finer disaggregated rig types. Similarly, the standard deviation of residual prices is \$11,000 per day when using aggregated rig types and \$9,000 per day when using disaggregated rig types. The high unexplained price variation in the data is consistent with a model of search frictions where the law of one price does not hold. Recent papers that document a similar magnitude of price dispersion in firm-to-firm search markets are those by Salz (2022) and Brancaccio et al. (2023).

*Documenting instances of mismatch.*—I preview the bottom-line results in the paper with an exercise that documents instances of mismatch by combining the raw data with selected parameters of the model, in the following way: I take the observed matches in each period and reallocate the rigs and wells in these matches optimally, using a linear sum assignment algorithm. For example, if there is a new match between a high-efficiency rig and a simple well and simultaneously a new match between a low-efficiency rig and a complex well, the algorithm will reallocate these matches. I detail the algorithm in appendix C.1.<sup>10</sup>

I report the results from the above procedure in table 3. In this table I split the benefits to better matching into the bust versus the boom. I also test for differences in the average match value in the bust compared to the boom. There are two main findings. First, there are benefits to better matching across the cycle. In a bust, the average increase in match value is \$0.779 million; for comparison, the average payment to a rig for a new contract is around \$3 million. In a boom, the average increase in match value is \$0.59 million. Second, this return is countercyclical: the returns

<sup>10</sup> Whether this example of reallocation—which involves more assortatively matching the two sides of the market—is truly optimal depends on the underlying match value. Therefore, in order to compute the optimal matches, as well as quantify the degree of mismatch, I use the match values I later estimate in the model in this exercise. These match values convert a given rig-well match into a dollar figure. Beyond these match values, I place no additional assumptions on the data, using just the empirical matches and available rigs.

TABLE 3  
DOCUMENTING MISMATCH

	Change in Match Value (millions of USD)		
	Bust	Boom	Difference: Bust versus Boom
Optimal match versus empirical match	.779	.59	.188
<i>t</i> -test	.001***	.006***	.019**

NOTE.—Preview of full model-based results through documenting instances of mismatch by reallocating empirical matches to optimal matches. I measure the degree of mismatch using the estimated match values from the model. I report the average change at the contract level (for comparison, the average payment to a rig for a new contract is around \$3 million). I split the results into the improvements to matching in the bust, the boom, and the difference in the boom-bust change. I also report *p*-values from a *t*-test for the difference in mean match values.

\*\*  $p < .05$ .

\*\*\*  $p < .01$ .

to better matching are higher in the bust than in the boom by \$0.188 million, which is consistent with the sorting effect.

### III. The Model: Sequential Search with Booms and Busts

#### A. Environment

*Agents.*—Agents are capital owners (owners of rigs) and projects (potential wells). The characteristics of a project are  $x = (x_{\text{complexity}}, x_{\text{quantity}}, \tau)$ . Here,  $x_{\text{complexity}}$  is the complexity of a project,  $x_{\text{quantity}}$  is the quantity of hydrocarbons (oil and gas), and  $\tau$  is the duration of the project in months. I do not directly include the water depth in these characteristics because it is part of the well complexity index  $x_{\text{complexity}}$ .

There are  $K_t$  draws of potential projects in each period, which are undrilled leases in the US Gulf of Mexico. The dependence on  $t$  is used to capture the fact that the number of potential projects may be changing over time. For example, an increase in the gas price may induce drillers to revisit old prospects or to be more likely to explore new tracts. Each of these potential projects has characteristics drawn from  $f_x$ , the probability density of potential projects.

Capital differs in its efficiency  $y \in Y = \{\text{low, mid, high}\}$ . Capital is either available to match or under contract. Only available capital can match with a project, and I denote the amount of available capital of type  $y$  at time  $t$  by  $n_{y,t}$ .

*Timing.*—The model is dynamic, and 1 period in the model is 1 month.<sup>11</sup> To keep notation concise, let the subscript  $t$  represent objects at the time  $t$  state  $s_t$ . The timing in each period is listed below:

<sup>11</sup> I verify in table A-10 that halving the period length does not affect the results substantially.

1. *Contract extensions.* Existing matches are extended with probability  $\eta_{xyt}$ , which is dependent on the state as well as the value of a particular match.
2. *Entry.* The set of potential projects is composed of  $K_t$  draws from a distribution  $f_x$ . Each potential project chooses whether to enter and search for capital. Denote the probability of entry for a type  $x$  project as  $e_{xt}$ .
3. *Search.* Each type of capital is located in a submarket. Meetings are determined probabilistically within each submarket as a function of the market tightness  $\theta_{yt}$  (the ratio of available capital to the mass of searching projects). Figure 5 provides a diagram of the search and matching process. Projects are able to direct their search toward a particular capital submarket using a search technology. Denote the probability that a type  $x$  project targets type  $y$  capital at time  $t$  with the search technology as  $\omega_{xyt}$ . Using the above notation, the market tightness can also be formally defined as  $\theta_{yt} = n_{yt} / (K_t \times \int \omega_{xyt} e_{xt} f_x dx)$ .
4. *Matching.* If a project owner contacts a capital owner, then agents choose whether to match. Prices are determined by Nash bargaining, and since this implies perfectly transferable utility, a match will be accepted if the total match surplus is positive. Therefore, define the acceptance set as  $A_{yt} = \{x : S_{xyt} \geq 0\}$ . If capital is matched, then it cannot match for the duration of the contract ( $\tau$  periods). If agents choose not to match, then projects exit the market immediately and the capital is available to match in the next period.<sup>12</sup> Note that in appendix E.3, I run robustness checks around the assumption of myopic projects and find that relaxing this assumption does not substantially change the results.

*Value of a match.*—I use the following specification for the per-period value of a match  $k$  periods after the time  $t$  that the match is created:

$$v_{xyt,k} = m_{0,y} + m_{1,y} \times x_{\text{complexity}} + m_2 \times \mathbb{E}_t[g_{t+k}]x_{\text{quantity}}, \quad (2)$$

so the total value of a contract is  $\sum_{k=0}^{\tau-1} \beta^k v_{xyt,k}$ . The above equation can be broken down into two main components. The first component is the match value added:  $m_{0,y} + m_{1,y} \times x_{\text{complexity}}$ . Here,  $m_{0,y}$  and  $m_{1,y}$  are coefficients that vary with rig type. This equation captures complementarities

<sup>12</sup> The assumption that well owners exit immediately if unmatched is based on the fact that well owners tend to wait until the end of their lease to drill a well and so cannot continue to search. Previous literature suggests that well owners do this because they are waiting to see whether the drilling of neighboring leases reveals good information about a project (Hendricks and Kovenock 1989; Hendricks and Porter 1996). If the lease elapses without drilling taking place, then the well owner forfeits the rights to the lease, which leads to drilling at the end of the lease (this fact is also documented for the onshore oil and gas industry in Herrnstadt, Kellogg, and Lewis 2024).

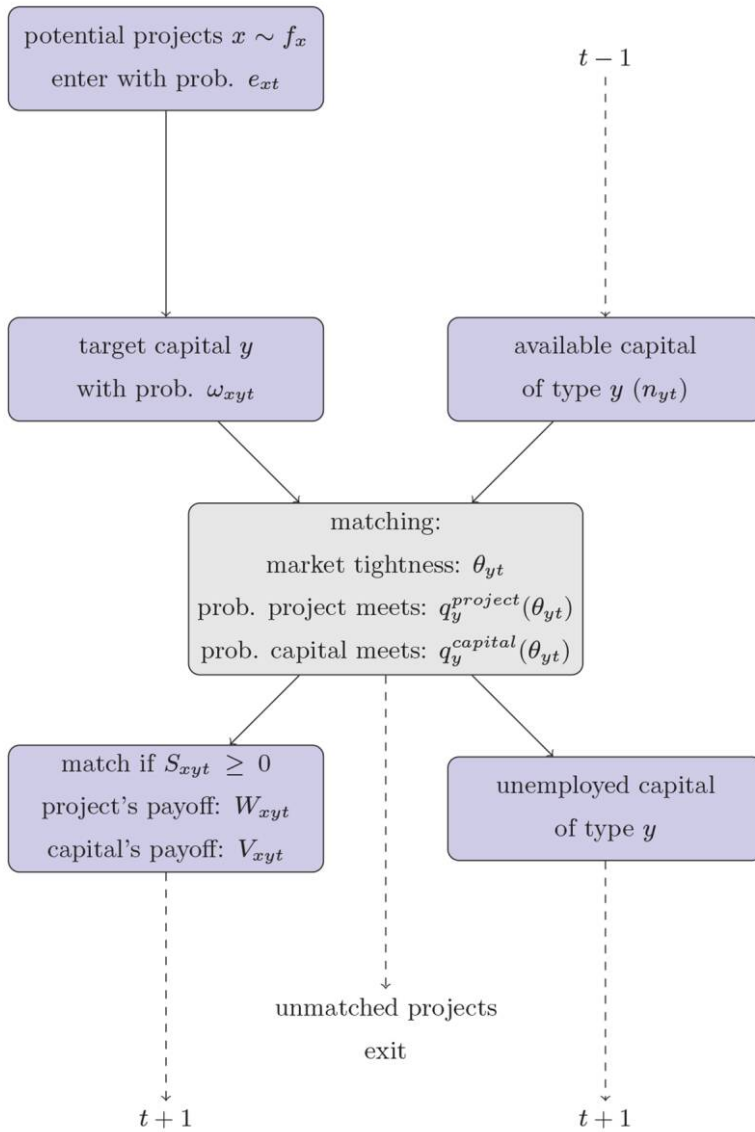


FIG. 5.—Search and matching within each submarket. At the beginning of each period, there is a distribution of searching projects and available capital  $n_{yt}$ . The searching projects first choose which type of capital to target. Meetings are determined randomly within each submarket and are dependent on the market tightness  $\theta_{yt}$ . Finally, agents choose whether to match based on whether the total surplus of a match is positive ( $S_{xyt} \geq 0$ ).

between rig type and well type through  $m_{1,y}$ . For example, a low-specification rig drilling more complex wells may reduce the match value through higher costs in the form of blowouts or extra materials after a drilling incident. On the other hand, if high-efficiency capital is well suited to undertaking complex projects, then  $m_{1,y}$  will be high. These parameters will determine how beneficial positive sorting is for welfare. For example, in a static setting with no search frictions, positive sorting is the optimal allocation if the match value is supermodular ( $m_{1,\text{high}} > m_{1,\text{mid}} > m_{1,\text{low}}$ ; Becker 1973).

The second component is  $m_2 \times \mathbb{E}_t[g_{t+k}]x_{\text{quantity}}$ . This component captures the expected total value of oil and gas that is produced. The variable  $g_{t+k}$  is the gas price at the period  $t + k$ . Since the covariate  $x_{\text{quantity}}$  is the ex ante quantity of hydrocarbons in the well (proxied by the maximum bid in the lease auction and then converted to a quantity, as discussed in the previous section), I include a parameter  $m_2$ , which is defined as the weight that agents put on this ex ante proxy when making decisions.

Note that the quantity of oil and gas extracted from the well does not depend on the rig type. Rather, the quantity of hydrocarbons that a well produces is dependent on geological features. Consistent with this assumption, the focus of industry practitioners and the engineering literature is on how rig choices and well design affect extraction costs (e.g., Hossain 2015). The expected value of oil and gas scales with the length of the contract since longer contracts usually involve constructing multiple similar wells over the same oil and gas deposit rather than a single well being drilled over many periods. For example, the average well in the sample takes 22.1 days from when the drill enters the sea floor to when it reaches the target depth (from the spud date to the depth date) and an additional few days to complete (cap and run in the production tube), which is approximately 1 month in total and 1 period in the model. Drill times are relatively similar across wells; for example, the 0.75 quantile is 26.0 days.

*Summary.*—Agents make three main choices in the model (with the rest of the model determined endogenously in equilibrium): a project entry decision, a project targeting decision, and a decision on whether to match if agents successfully contact each other. Overall, the model focuses on the dynamic trade-off for capital owners.

*Comparison to previous industrial organization work on search and matching models.*—The key difference I need to contend with in my setting is two-sided vertical heterogeneity. This contrasts with previously studied markets like taxis (e.g., Buchholz 2022) and bulk shipping (e.g., Brancaccio, Kalouptsi, and Papageorgiou 2020), where agents are relatively homogeneous. Because of this feature, the model departs from the past industrial organization literature in search and matching models in two main ways. First, I allow for search to be (partially) directed, where heterogeneous

projects can target the type of capital that they are best suited to match with. Second, I account for the fact that matches can be rejected, so agents have acceptance sets.

My framework also shares some elements with previous work. Most notably, once projects have decided which type of capital to target, meetings take place within a submarket in a way similar to how they would within an individual location in a taxi market or a port in the bulk shipping market.<sup>13</sup> Within a location, distance is assumed not to explicitly factor into rig selection; as previously mentioned and also discussed in appendix A.3, this seems to be a reasonable assumption.

### B. Demand for Capital

*Payoffs.*—First, I consider the profits to a type  $x$  project matching with type  $y$  capital. Intuitively, the profit will depend on the per-period match value and the per-period capital price. In addition, because contracts can be extended, agents will take these future contract extensions into account as well when matching. Overall, the value to a project owner from matching is

$$W_{xyt} = \underbrace{\sum_{k=0}^{\tau-1} \beta^k [v_{xyt,k} - p_{xyt}]}_{\text{value of the initial contract}} + \underbrace{\beta^\tau \mathbb{E}_t [\eta_{xy,t+\tau} W_{xy,t+\tau}]}_{\text{extension value}}. \quad (3)$$

The project owner's value of matching  $W_{xyt}$  can be decomposed in the following way: For each period of the  $\tau$  length contract, the project owner receives the match value  $v_{xyt,k}$  minus the price  $p_{xyt}$  to hire the capital. The contract will be extended with probability  $\eta_{xy,t+\tau}$ , which is dependent on the state at time  $t + \tau$  and the value of the match. In appendix D.1 I show that the assumption that the extended contract has the same duration as the initial contract is reasonable.

*Partially directed search.*—I first discuss how search operates once entry has occurred, and then I turn to the entry decision. In the search process, potential projects choose which capital submarket to search in. The choice of submarket depends on the characteristics of the project, as well as the probability of matching within each submarket, which is governed by the matching technology  $q_y^{\text{project}}(\theta_{yt})$ , among other things. For a type  $x$  project, denote the (expected) value of searching in the type  $y$  capital submarket as  $\pi_{xyt} = q_y^{\text{project}}(\theta_{yt}) W_{xyt}$ .

I allow for a flexible search technology: partially directed search. To derive this technology from individual decisions, denote each unit of available capital by  $j$  and the corresponding type as  $y_j$ . Similarly, denote each

<sup>13</sup> In this way, fig. 5, which sets out how meetings take place within a submarket, can be compared to a similar figure in Buchholz (2022).

searching project by  $i$  and its corresponding type by  $x$ . In the special case where search is perfectly directed, then each potential project  $i$  will choose  $j$  to solve  $\max_j \pi_{x,y,t}$ . In my setting, I allow for a more flexible search technology by instead modeling potential projects targeting capital based on a perceived value  $\hat{\pi}_{x,y,t}$ , which is defined as

$$\hat{\pi}_{x,y,t} = \pi_{x,y,t} - \gamma_1 1[x_i \notin A_{y,t}] + \epsilon_{ijt}^{\text{target}}. \quad (4)$$

I assume that  $\epsilon_{ijt}^{\text{target}}$  is drawn from an independent and identically distributed (i.i.d.) type 1 extreme value distribution with scale parameter  $1/\gamma_0$ . The interpretation of  $\gamma_0$  and  $\gamma_1$  is that they are targeting parameters that index how precisely a project can target capital, and  $1[x \notin A_{y,t}]$  is an indicator function for whether the match will be rejected. I allow for targeting to be responsive to both whether the match will be rejected (the parameter  $\gamma_1$ ) and the overall quality of the match  $\gamma_0$ . The motivation for including the  $\gamma_1$  component is that whether a match could be rejected might be more salient to capital owners than other features of the match; I allow the data to determine whether this is the case.

Aggregating the conditional choice probabilities that result from  $\max_j \hat{\pi}_{x,y,t}$  across all capital of the same type and dispensing with the  $i$  and  $j$  subscripts results in the probability of a project of type  $x$  targeting a rig of type  $y$ :

$$\omega_{xyt} = \frac{n_{yt} \exp(\gamma_0[\pi_{xyt} - \gamma_1 1[x \notin A_{yt}]])}{\sum_{k \in Y} n_{kt} \exp(\gamma_0[\pi_{xkt} - \gamma_1 1[x \notin A_{kt}]])}. \quad (5)$$

This search technology is more flexible than the typical assumptions of random search or directed search, which are both used in search models. At the extremes, this specification nests random search (at  $\gamma_0 = 0$ , where projects contact capital completely at random) and directed search (as  $\gamma_0 \rightarrow \infty$ , where projects can perfectly identify the best match).

*Entry.*—Before making the targeting decision, each potential project chooses whether to enter. This decision is  $\max\{\sum_{k \in Y} \omega_{xkt} \pi_{xkt} - c + \epsilon_t^{\text{entry}}, \epsilon_t^{\text{no entry}}\}$ . Here,  $c$  is the entry cost and  $\epsilon_t^{\text{entry}}$  and  $\epsilon_t^{\text{no entry}}$  are drawn from an i.i.d. type 1 extreme value distribution. The first term in the maximization is the expected benefit of entering. The entry cost  $c$  takes into account the cost of submitting a permit (which includes a detailed project design) to the regulator, among other things. The resulting conditional choice probability that a project enters is

$$e_{xt} = \frac{\exp(\sum_{k \in Y} \omega_{xkt} \pi_{xkt} - c)}{1 + \exp(\sum_{k \in Y} \omega_{xkt} \pi_{xkt} - c)}. \quad (6)$$

*Demand for capital.*—Aggregating up the individual project entry and targeting decisions result in the demand for capital. Denote  $h_{xyt}$  as the

probability that type  $y$  capital will be contacted by a type  $x$  project. This is given by

$$h_{xyt} = q_y^{\text{capital}}(\theta_{yt}) \times \frac{\omega_{xyt} e_{xt} f_x}{\int_z \omega_{zyt} e_{zt} f_z dz}, \quad (7)$$

and the probability that capital is not contacted by any project is  $h_{\emptyset yt} = 1 - q_y^{\text{capital}}(\theta_{yt})$ .

The above setup allows for considerable flexibility in how demand changes in booms and busts along two dimensions. First, the probability of capital finding a project may increase when the market moves from a bust to a boom if the number of potential project draws  $K_t$  increases in a boom. Second, the distribution of trading opportunities  $h_{xyt}$  will change as a result of different projects entering and different targeting behavior. Given demand for capital, I now turn to the capital owners' problem.

### C. Capital Owners' Problem

If capital is contacted by a project, it faces the following trade-off. Accept the match—and be unable to match for the duration of the contract—or search again for a better match after 1 period:  $\max\{V_{xyt}, \beta \mathbb{E}_t U_{y,t+1}\}$ . Here,  $V_{xyt}$  is the profit from matching and is given by

$$V_{xyt} = \sum_{k=0}^{\tau-1} \beta^k p_{xyt} + \beta^\tau \mathbb{E}_t [\eta_{xy,t+\tau} V_{xy,t+\tau} + (1 - \eta_{xy,t+\tau}) U_{y,t+\tau}]. \quad (8)$$

The profit from matching  $V_{xyt}$  can be decomposed as follows: The rig will first receive the value of the contract, which is the per-period price  $p_{xyt}$  for  $\tau$  periods. When the contract is complete, the rig owner receives  $V_{xy,t+\tau}$  if the contract is extended. If the contract is not extended, then the rig will be available to search again and will receive  $U_{y,t+\tau}$ .

The value of searching is

$$U_{yt} = \underbrace{\int_z \max\{V_{zyt}, \beta \mathbb{E}_t U_{y,t+1}\} h_{zyt} dz}_{\text{expected value of a meeting}} + h_{\emptyset yt} \underbrace{\beta \mathbb{E}_t U_{y,t+1}}_{\text{no meeting}}. \quad (9)$$

The first term is the expected value of a meeting; capital meets a particular project type with probability  $h_{zyt}$  and it will choose whether to match with it. If capital is not contacted by a project (which happens with probability  $h_{\emptyset yt}$ ), then it will be unemployed for one period but will be available the following period.

*Bargaining.*—If capital and a project match, then prices are determined by generalized Nash bargaining, where  $\delta \in [0, 1]$  is the bargaining weight:

$$p_{xyt} = \operatorname{argmax}_{p_{xyt}} [V_{xyt} - \beta \mathbb{E}_t U_{y,t+1}]^\delta [W_{xyt}]^{1-\delta}. \quad (10)$$

Note that prices  $p_{xyt}$  are embedded in the value of matching for capital  $V_{xyt}$  and projects  $W_{xyt}$ . The outside option for the capital is to search again the following period for another match, with value  $\beta \mathbb{E}_t U_{y,t+1}$ . Since the project will exit immediately if it is not matched, the project's outside option is 0.

*Total surplus and contract extensions.*—The total surplus of a match is given by  $S_{xyt} = W_{xyt} + V_{xyt} - \beta \mathbb{E}_t U_{y,t+1}$ . I assume that the contract will be extended if the following two conditions are satisfied: (i) the match surplus is still positive at the time of extension and (ii) drilling on the original prospect reveals good information that induces the contract to be extended, which I model as a draw from a Bernoulli distribution with parameter  $\eta$ . These two conditions imply that the probability of an extension is  $\eta 1_{[S_{xy,t+\tau} \geq 0]}$ .

#### D. Transitions and States

*Transitions.*—At the start of each period, rigs either are unemployed or are currently matched. If a rig is currently matched, denote  $\tau_k$  as the number of periods remaining on its contract. Matches with  $\tau_k = 0$  are possibly extended. Rigs that are unemployed or whose contracts are not extended are available to match. Rigs that do not find a new match become unemployed. At the end of each period,  $\tau_k$  counts down by 1.

*States.*—The detailed industry state in each period is the price in dollars for natural gas  $g$ , the distribution of current matches, and the distribution of unemployed rigs. Modeling firms as keeping track of the full industry state would be computationally difficult because of the curse of dimensionality. I assume instead that firms keep track of their own state and some moments of the industry state. This is similar to a moment-based Markov equilibrium (Ifrach and Weintraub 2017). I assume that these moments that characterize an agent's beliefs about state  $s$ , are

$$s_t = [g_t, n_{\text{low},t}, n_{\text{mid},t}, n_{\text{high},t}]. \quad (11)$$

Here,  $n_{y,t}$  is the number of available rigs of type  $y$  at time  $t$ , and  $g_t$  is the natural gas price at time  $t$ . A rig is available to match if either it enters the period unemployed or there are zero periods remaining on its contract and the match is not extended. I choose these states because these statistics are commonly reported in the annual reports of rig owners and are used by firms that track the industry to describe the state of the market. Note that while I assume that the agents are relatively small, and thus take the industry state as given, the actions of the many individual agents scale up to the aggregate state.

I model agents' beliefs about equilibrium industry state transitions as an AR(1) process:  $s_t = R_0 + R_1 s_{t-1} + \epsilon_t$ . I assume that rig transitions are deterministic, so the only stochastic component in the model is the gas price error term, which implies that  $\Sigma = \text{diag}(\sigma_\epsilon, 0, 0, 0)$ . In the  $R_1$  matrix, I set the coefficients in the  $g_t$  updating rule to 0, except for the coefficient on  $g_{t-1}$ . That is, while changes in the natural gas price cause changes in rig availability in the Gulf of Mexico, rig availability in the Gulf of Mexico does not affect the global natural gas price.

### E. Equilibrium

Equilibrium is defined as a set of prices  $p_{xyt}$ , capital availability  $\{n_{yt}\}_{y \in \{\text{low, mid, high}\}}$ , demand for capital  $h_{xyt}$ , targeting weights  $\omega_{xyt}$ , entry probability  $e_{xt}$ , submarket tightness  $\{\theta_{yt}\}_{y \in Y}$ , and agents' state transition beliefs that satisfy at each state  $s_t$ :

1. The targeting weights  $\omega_{xyt}$ , entry probability  $e_{xt}$ , and submarket tightness  $\{\theta_{yt}\}_{y \in Y}$ , determined by equations (3)–(6).
2. Demand for capital  $h_{xyt}$ , determined by equation (7).
3. Agents optimally choosing whether to accept or wait if matched using equations (8) and (9).
4. Equilibrium prices  $p_{xyt}$  determined by Nash bargaining: equation (10).
5. Updating the rule for the distribution of capital  $\{n_{yt}\}_{y \in Y}$  according to the description in section III.D.
6. Beliefs about the future evolution of states given by an AR(1) process.

## IV. Estimation and Identification

### A. Overview

I present all the parameters in table 4 and now discuss the specification of model objects, as well as how I calibrate certain parameters.

*Calibrated parameters.*—I calibrate the discount parameter to  $\beta = 0.99$  (recall that 1 period is 1 month). I calibrate the entry cost  $c$  using industry studies that decompose drilling expenditure into entry costs (prespud costs) versus other costs. Using the average total payment to a rig owner as my measure for other drilling costs, I calibrate  $c = \$1.32$  million.<sup>14</sup>

<sup>14</sup> Specifically, I rely on Hossain (2015), which puts prespud drilling costs at around 18% of total expenses. Using this number and setting other expenses to the mean total payment to a rig (including extensions), which is around \$6 million, I calibrate the entry cost as  $c = (0.18/0.82) \times 6 = \$1.32$  million.

TABLE 4  
OVERVIEW OF HOW MODEL COMPONENTS ARE COMPUTED

Object	Parameters	Method
Discount rate, monthly	$\beta$	Calibrated: preliminary
Entry cost	$c$	Calibrated: preliminary
State transition beliefs	$R_0, R_1, \sigma_e$	Estimated: step 1
Bargaining weight	$\delta$	Calibrated: step 1
Demand distribution	$\tau_2, \tau_3, \tau_4, \mu, \sigma, \rho_0, \rho_1, \rho_2, \rho_3$	Estimated: step 2
Demand draws	$k_0, k_1$	Estimated: step 2
Match value	$\{m_{0,y}, m_{1,y}\}_{y \in Y}, m_2$	Estimated: step 2
Extension parameter	$\eta$	Estimated: step 2
Targeting parameters	$\gamma_0, \gamma_1$	Estimated: step 2
Meeting technology	$\{a_y\}_{y \in Y}$	Estimated: step 2

NOTE.—Overview of the parameters to be estimated or calibrated.

*Empirical specification: meeting technology.*—For the meeting technology within each capital submarket, I use the following parametric forms:

$$q_y^{\text{capital}}(\theta_{yt}) = \min \left\{ 1 - \exp \left( \frac{-a_y}{\theta_{yt}} \right), 1/\theta_{yt} \right\}, \quad (12)$$

$$q_y^{\text{project}}(\theta_{yt}) = \min \left\{ \theta_{yt} \left( 1 - \exp \left( \frac{-a_y}{\theta_{yt}} \right) \right), 1 \right\}. \quad (13)$$

This meeting technology can be derived as an approximation to an urn-ball matching function with a large number of agents (for a derivation, see Petrongolo and Pissarides 2001). I also bound the meeting technology to prevent the model from predicting more matches than there is available capital.

*Empirical specification: demand.*—I use the specification that there are  $K_t = k_0 + k_1 g_t$  potential projects in each period, where  $g_t$  is the natural gas price and  $k_0$  and  $k_1$  are parameters. I place the following parametric assumptions on the distribution of potential wells  $f_x$ :

- The quantity of hydrocarbons is a third-dimensional polynomial of the well complexity:  $x_{\text{quantity}} = \rho_0 + \rho_1 x_{\text{complexity}} + \rho_2 (x_{\text{complexity}})^2 + \rho_3 (x_{\text{complexity}})^3$ , where  $\rho_0, \rho_1, \rho_2$ , and  $\rho_3$  are parameters. I run an ordinary least squares regression to recover the parameters  $\rho_0, \rho_1, \rho_2$ , and  $\rho_3$ .
- Contract durations are for 2, 3, or 4 months and are distributed independently of the other covariates with probability weights  $(\tau_2, \tau_3, \tau_4)$ , where  $\tau_4 = 1 - \tau_2 - \tau_3$ .
- Well complexity is distributed as a truncated normal  $x_{\text{complexity}} \sim TN(\mu, \sigma)$ , where the parameters  $\mu, \sigma$  need to be estimated. I choose the minimum of the truncated normal as  $x_{\text{complexity}} = 0$  and the maximum as  $x_{\text{complexity}} = 2.15$ .

### B. Estimation

I estimate the model in two steps, similar to much of the literature on dynamic games (e.g., Bajari, Benkard, and Levin 2007). In the first step I compute conditional choice probabilities and state transitions from the data. In the second step the parameters are estimated via the simulated method of moments. A point of departure from the standard two-step approach is that I show that the value function for searching  $U_{st}$  can also be computed in the first step directly from the data, which then serves as an input into the estimation of parameters in later steps. This is an extension of recent approaches in the industrial organization firm dynamics literature to cases where short-term contract data are available; for example, Kalouptisidi (2014) uses data on secondhand sales to estimate value functions.

*Step 1.*—I estimate the beliefs over the state transitions using maximum likelihood and the data on empirical state transitions. The value of searching can then be written nonparametrically through forward simulation of these state transitions, data on matches, data on prices, and data on the probability of extending a contract; I provide a more formal proof of this in appendix B.2. In appendix C.2 I provide more details about how I construct the objects that the value functions can be built from and detail the forward simulation algorithm.

I then calibrate the bargaining parameter using a strategy similar to that of Brancaccio, Kalouptisidi, and Papageorgiou (2020). I focus on the year 2005, when the market was approximately in a steady state, with the gas price near its long-run average. I compute a nonstochastic steady state of the model. Then, using external data from the annual reports of the largest oil and gas companies in the Gulf of Mexico, I compute total revenue and operating margins. Intuitively, the bargaining weight is set so that the split of surplus between capital owners and project owners is consistent with these operating margins. I provide more details in appendix B.4.

*Step 2: simulated method of moments.*—I simulate the model from January 2000 to December 2009. The simulation algorithm computes the equilibrium entry and targeting choices of potential wells, as well as the matching accept/reject decisions and contract extensions, given the value functions that were computed in step 1. I provide complete details on the simulation algorithm, as well as the implementation of the simulated method of moments, in appendix C.5.

### C. Identification and Choice of Moments

I now discuss the intuition behind how the parameters are identified and the choice of moments. I leave a more rigorous discussion of identification to appendix B.5. Overall, a major challenge is that the matching patterns in the data (e.g., in fig. 4A) could be generated by compositional

changes in the set of searching wells or by the sorting effect. Therefore, among other things, I show that acceptance sets and the targeting parameters can be separately identified from the distribution of wells.

*Identifying parameters underlying match surplus and acceptance sets.*—I identify the match value parameters ( $m_{0,y}$ ,  $m_{1,y}$ , and  $m_2$ ) using the price data for matches. Intuitively, after adjusting for the outside option and the bargaining parameter  $\delta$ , higher prices identify a higher-value match. I operationalize this idea by first rearranging the Nash bargaining solution in the following way, which I derive in appendix B.3:

$$p_{xyt} = (1 - \delta)z_{xyt} + \delta m_{0,y} + \delta m_{1,y}x_{\text{complexity}} + \delta \left[ \frac{\sum_{k=0}^{\tau-1} \beta^k \mathbb{E}_t [g_{t+k}]}{\sum_{k=0}^{\tau-1} \beta^k} \right] x_{\text{quantity}}. \quad (14)$$

Here,  $z_{xyt}$  is an object that can be constructed from the data that include the outside option. Based on this equation, in estimation I run the following auxiliary regression and obtain the  $\hat{\beta}$  coefficients:

$$p_{xyt} - (1 - \delta)z_{xyt} = \hat{\beta}_{0,y} + \hat{\beta}_{1,y}x_{\text{complexity}} + \hat{\beta}_2 g_t x_{\text{quantity}}. \quad (15)$$

I run a similar regression using the model and match the  $\hat{\beta}$  coefficients as moments to identify the match value parameters. For simplicity, I use just the gas price in the first period of the contract in this regression. I also include two additional price moments that correspond to the price difference between high/mid rigs and mid/low rigs; these moments ensure that the model also generates the ordering in average prices as rig specification increases. The final parameter of the match surplus that remains is the extension probability  $\eta$ , which I identify by including a moment for the average probability of extending a contract over the sample period.

With the match value parameters identified and the rig's value of searching computed from step 1, I can then construct the match surplus. In addition, acceptance sets can be constructed since  $A_{yt} = \{x : S_{xyt} \geq 0\}$ . I detail the match surplus computational algorithm in appendix C.3.

*Identifying targeting parameters.*—I first discuss how the targeting parameter  $\gamma_0$  is identified; this parameter governs how responsive targeting is to the match surplus and nests random search and directed search. I pin this parameter down by including moments that capture the empirical sorting patterns, specifically, the average match of low-, mid-, and high-specification capital in booms and busts (six moments). Under random search  $\gamma_0 = 0$ , sorting patterns across rig types are entirely governed by acceptance sets; these acceptance sets are identified using previous arguments. If  $\gamma_0 > 0$ , then sorting can also occur within acceptance sets, with higher  $\gamma_0$  leading to stronger sorting. Therefore,  $\gamma_0$  can be identified by matching the empirical sorting moments after controlling for acceptance sets.

I include a moment for the average utilization in 2006 for high-specification rigs. This helps to pin down the targeting parameter  $\gamma_1$ : a model with  $\gamma_1 = 0$  is unable to fully match empirical utilization rates in time periods following a boom like 2006 where the acceptance sets are constrained (because of a low number of available rigs) but the arrival rate of new projects is also low. Higher values of  $\gamma_1$  allow for wells to avoid these matches, resulting in fewer rejections and a higher capital utilization.

*Identifying meeting technology parameters.*—In appendix B.5 I show that the market tightness term  $\theta_{yt}$  can be identified given the above parameters. Then the meeting technology parameter  $a_y$ —which relates how  $\theta_{yt}$  affects the probability of capital matching  $q_y^{\text{capital}}(\theta_{yt}) = \min\{1 - \exp(-a_y/\theta_{yt}), 1/\theta_{yt}\}$ —can be identified from the probability of matching in a single period  $t$ . Therefore, I include moments related to the probability of matching: the mean utilization of each capital type (three moments).

*Identifying potential project parameters.*—More potential project draws  $K_t$  decrease the market tightness  $\theta_{yt}$ . Therefore, the potential project draw parameters  $k_0$  and  $k_1$  can be identified by matching variation in the probability of capital matching across periods. Hence, I include moments for the covariance of utilization and the gas price for each capital type (three moments), and the variance of utilization for each capital type (three moments).

The remaining parameters to identify relate to the distribution of potential wells  $f_x$ . Given that the rest of the model is identified, including acceptance sets and the targeting weights,  $f_x$  can now be identified by matching the distribution of observed matches. Therefore, I include the variance of well complexity matches (one moment), as well as the previously discussed moments relating to the mean well complexity matches for each rig type in booms and busts. I also include the probability of observing a 2-month contract and a 3-month contract (two moments).

## V. Results

*Constructing the value of searching  $U_{yt}$ .*—The results for the beliefs over the state transitions are as follows (standard errors are shown in brackets; recall that the states are ordered as  $s_t = [g_t, n_{\text{low},t}, n_{\text{mid},t}, n_{\text{high},t}]$ ):

$$R_0 = \begin{bmatrix} 0.81 & (0.36) \\ 6.95 & (1.86) \\ 4.62 & (2.14) \\ 7.02 & (1.72) \end{bmatrix}, \quad R_1 = \begin{bmatrix} 0.88 & (0.04) & 0 & 0 & 0 \\ -0.41 & (0.15) & 0.71 & (0.08) & 0.07 & (0.09) & -0.03 & (0.08) \\ -0.34 & (0.15) & 0.2 & (0.09) & 0.48 & (0.09) & 0.21 & (0.08) \\ -0.4 & (0.15) & -0.2 & (0.07) & 0.23 & (0.08) & 0.48 & (0.08) \end{bmatrix}.$$

(16)

Also, the parameter  $\sigma_\epsilon = 1.15$  (0.06). Since all the eigenvalues of  $R_1$  lie within the unit circle, the transition matrix is stationary.

Figure 6 illustrates the outcome of the forward simulation procedure to obtain  $U_{y,t}$ . The value functions increase in booms and fall in busts, which is consistent with there being more matching opportunities when the gas price is high. The gray lines correspond to agents' forecast of the value of searching over the next 12 months, for example,  $\mathbb{E}_t U_{t+2}(y)$ , and so forth. The gray lines indicate that agents have mean-reverting expectations about the value of searching, which is not surprising because the state transitions are also mean reverting.

*Value of a match parameters.*—Table 5 contains the results for the value of a match. The estimates for the  $m_{0,y}$  terms imply that for very simple wells, low-specification rigs generate relatively higher match values. This occurs because—from the perspective of a well owner drilling a simple well—high-specification rigs are overbuilt, featuring complicated on-board technology that is costly to monitor. Next, consider the estimates for  $m_{1,y}$ ; comparing these values by rig type indicates that the match value

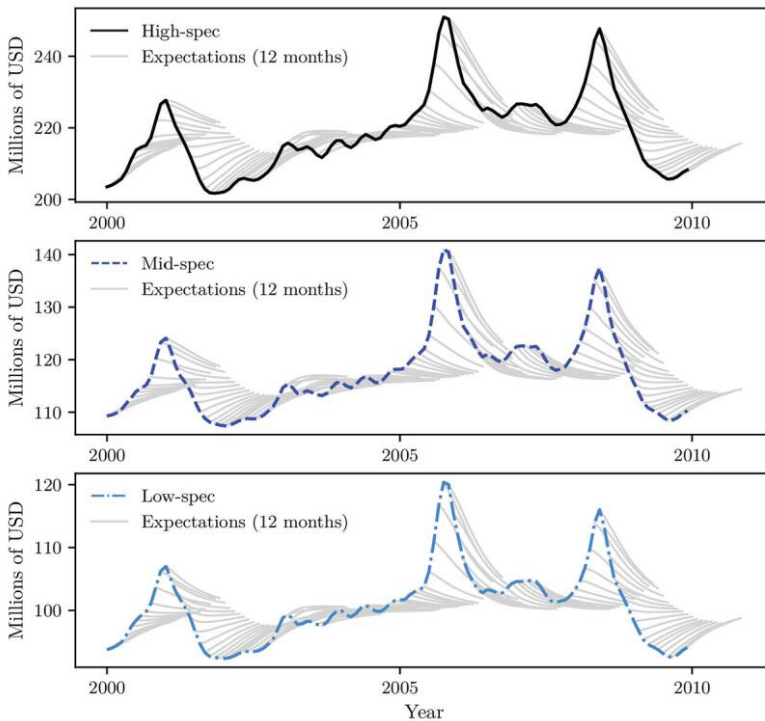


FIG. 6.—Rig's value of searching  $U_{y,t}$ . Points on the graph are plotted monthly. The gray lines correspond to the 12-month future beliefs of the value of searching.

TABLE 5  
ESTIMATED PARAMETERS

Variable	Symbol	Value	
Match value, extension	$m_{0,low}$	88.4 (74.2 to 98.8)	
	$m_{0,mid}$	72.6 (56.8 to 88.9)	
	$m_{0,high}$	57.2 (47.4 to 67.9)	
	$m_2$	3.7 (.7 to 10.1)	
	$m_{1,low}$	-37.5 (-45.7 to -29.3)	
	$m_{1,mid}$	.7 (.4 to 1.2)	
	$m_{1,high}$	40.5 (25.0 to 56.6)	
	$\eta$	.38 (.35 to .4)	
	Demand	$\mu$	.68 (.52 to .77)
		$\sigma$	.72 (.57 to .95)
		$\rho_0$	.031 (.015 to .047)
		$\rho_2$	-.024 (-.044 to -.004)
		$\tau_2$	.69 (.65 to .73)
$\tau_3$		.2 (.17 to .23)	
$\rho_1$		.037 (.001 to .073)	
$\rho_3$		.0028 (.0003 to .0053)	
Entry cost, bargaining parameter		$c$	\$1.32 million
		$\delta$	NA
Potential project draws	$k_0$	.37 NA	
	$k_1$	22.9 (11.1 to 31.0)	
Meeting technology	$a_{low}$	8.0 (6.1 to 11.3)	
	$a_{mid}$	.44 (.31 to .62)	
	$a_{high}$	.57 (.41 to .71)	
Targeting parameter	$\gamma_0$	16.5 (8.02 to 25.12)	
	$\gamma_1$	.71 (.26 to 1.11)	
		1.43 (.51 to 2.25)	

NOTE.—All parameters are estimated using the simulated method of moments, except for estimates for  $\rho_0$ ,  $\rho_1$ ,  $\rho_2$ , and  $\rho_3$ , which are computed using the ordinary least squares (OLS) regression of  $x_{quantity} = \rho_0 + \rho_1 x_{complexity} + \rho_2 x_{complexity}^2 + \rho_3 x_{complexity}^3$ . Confidence intervals (95%) are shown in parentheses. An NA term in the confidence interval denotes a calibrated value. The confidence intervals are computed using 200 bootstrap replications, except for estimates for  $\rho_0$ ,  $\rho_1$ ,  $\rho_2$ , and  $\rho_3$ , which are computed using the standard errors from the OLS regression.

is supermodular. Finally, I find that the value weight  $m_2 = 3.7$ . Scaling up this per-day figure over 1 month implies that agents weight a \$1 million increase in this lease bid proxy to a \$0.111 million increase in the total match value.

From these value of a match estimates and estimates of capital's value of searching, I can construct acceptance sets. I plot the acceptance sets over time in figure A-4. The way that these acceptance sets shrink in booms depends primarily on the sign of  $m_{1,y}$ . While the acceptance sets for low- and high-specification rigs are intuitive, perhaps surprising is that mid-specification rigs appear to accept all matches because of a low value of  $m_{1,\text{mid}}$ . The implication of mid-specification rigs accepting all wells is that their matches do not change substantially in booms and busts; this is consistent with the empirical sorting patterns in figure 4.

*Demand and meeting technology parameters.*—Table 5 contains the estimated parameters from the simulated method of moments. Overall, the parameters seem reasonable. The estimated targeting parameter  $\gamma_0$  is 0.71. To get a sense of where this lies between random search and directed search, I consider the probability that a complex well (I set  $x_{\text{complexity}} = 2.0$ ) targets its optimal match (which is a high-specification rig) at approximately the average state.<sup>15</sup> In the model, this targeting probability is 0.34; under random search, this number is 0.23; and under directed search, this number is 1.0. Therefore, the search technology that best rationalizes the data is closer to random search than to directed search. In terms of the targeting parameter  $\gamma_1$ , I find that it is positive but relatively small.

For the matching efficiency parameters, the values of  $a_{\text{low}}$ ,  $a_{\text{mid}}$  indicate that matching in the corresponding submarkets is not perfectly efficient. In contrast, the value of  $a_{\text{high}}$  is quite high and quite close to frictionless matching in the high-efficiency capital submarket. For the remaining parameters (e.g., the mean and standard deviation of potential projects), it is difficult to interpret them in isolation.

*Model fit.*—Table A-6 provides a complete comparison of how the simulated moments fit the data. The model replicates the data well. I also provide out-of-sample fit exercises in appendix D.6.

## VI. Counterfactuals

I now use the model to perform three counterfactuals, which are designed to assess the efficiency of capital reallocation over the boom-bust cycle and to assess potential policies to improve matching. I first quantify the extent to which the sorting effect improves allocations. I then test

<sup>15</sup> Specifically, I choose the state halfway through the sample at January 2005, which is also between a boom and a bust.

how an intermediary or demand-smoothing policies would impact welfare in light of the sorting effect.

My measure of welfare is the total value of wells drilled minus entry costs. Denoting  $Y$  as the set of capital in the market and letting  $T = \{2000 : 1, \dots, 2009 : 12\}$ , total welfare is

$$\sum_{t \in T} (\{\text{total value of projects by } Y \text{ at } t\} - \{\text{no. projects entered at } t\} \times c - \text{OPEX}),$$

where OPEX is the total operating expenses of the rigs, which I set to be \$32,000 per day per rig.<sup>16</sup> I recompute the value functions in the counterfactuals where necessary, as well as agents' beliefs about state transitions. I leave the computational details to appendix C.

For each of the counterfactuals, I decompose the total effect into three components.

- *Quality effect.* The change in the value of matches keeping the number of matched rigs fixed in both the baseline and the counterfactual.
- *Quantity effect.* The value of the new rigs that are matched in the counterfactual (or the loss in value if more rigs are unmatched in the counterfactual).
- *Entry cost saving.* The change in the total entry cost in the counterfactual.

#### A. *Quantifying the Sorting Effect*

I first quantify how stronger sorting in booms increases welfare. Recall that the sorting effect arises because the option value of searching increases in a boom compared to a bust and therefore agents are more selective in matching in booms than in busts. Consequently, to quantify the sorting effect, I simulate an equilibrium that shuts down the two channels by which agents can be selective. First, I extend the acceptance sets to include all matches with positive match value, which prevents agents from rejecting matches based on changes in the outside option. Second, I set the targeting parameters  $\gamma_0 = \gamma_1 = 0$ , which shuts down the channel of agents using the search technology to selectively avoid rigs with high outside options.

I simulate the model using the empirical natural gas price. Starting from the no-sorting-effect counterfactual, I compute the change in welfare when moving to the market benchmark. I keep the composition of

<sup>16</sup> This figure comes from Kaiser and Snyder (2013), as the expenses for an operating jack-up rig in the US Gulf of Mexico 2010–11 as reported in the Hercules Offshore annual report. Hercules Offshore is a firm that owns and leases drilling rigs. Operating expenses include, e.g., routine rig maintenance.

searching wells the same in the no-sorting-effect counterfactual as in the market benchmark.

I plot the results in figure 7. Panel *A* plots the total change in welfare (joint profits). Welfare with the sorting effect is greater in every period, and the total increase is 12.0%. The effect is cyclical: the welfare increase in a boom is 7.3% compared to around 4.7% in a bust. Panels *B* and *C* decompose how the sorting effect increases welfare: there are fewer matches (which by itself decreases welfare by  $-8.2\%$ ), but the remaining matches are of higher quality because agents are more selective (which increases welfare by  $20.2\%$ ). Overall, the match quality effect dominates, which results in a net increase in welfare.

### *B. An Intermediary That Reduces Search Frictions*

Next, I study the potential gains from an intermediary. I need to take a stand on the exact nature of the intermediary in the marketplace. In summary, I use a greedy matching algorithm, which matches the set of

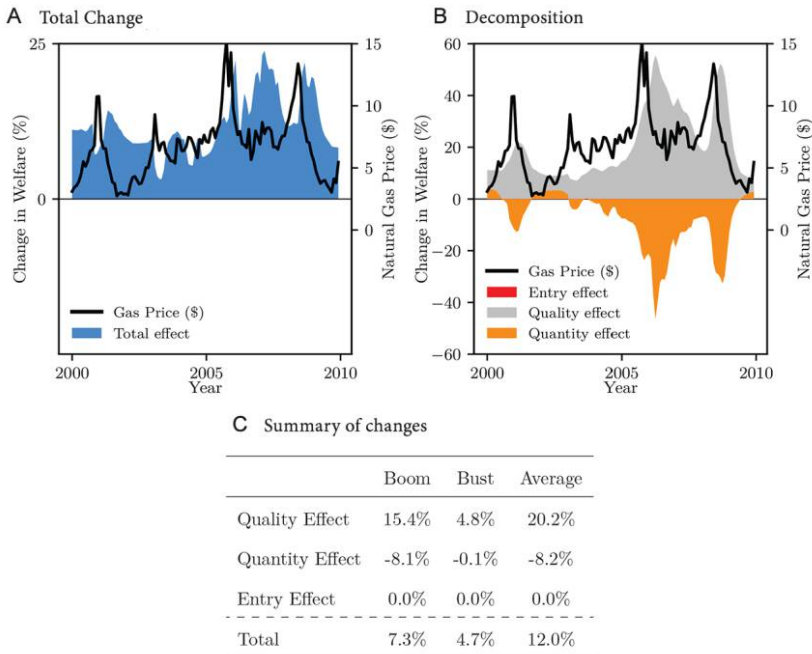


FIG. 7.—No-sorting counterfactual results. *A*, Total change. *B*, Decomposition. Shown is the change in welfare when moving from the no-sorting counterfactual to the market baseline. I keep the composition of searching wells fixed to the market benchmark, resulting in an entry effect of 0. The welfare in dollars at the market baseline is 5.0 billion.

entered wells to a submarket of available rig types in each period. The algorithm is greedy because it considers only the static match value when choosing which submarket to match each well to. One may ask about the extent to which including dynamic considerations could improve allocations, especially in light of the sorting effect. However, the sorting effect arises because of search frictions, and in this counterfactual these frictions are greatly reduced, which blunts the incentives to wait for a better match. In addition, the matching protocol is relatively simple, so it could be feasibly implemented by a real-world intermediary.

Conceptually, this intermediary can be thought of as an Uber for rigs, which introduces a vast improvement in the search technology of the industry. To facilitate a comparison with the sorting effect counterfactual, I also keep the composition of searching wells fixed. I leave details on the implementation algorithm to appendix C.7. Figure 8 illustrates the change in welfare due to an intermediary. Panel A shows that the intermediary increases welfare by around 51.0% over 2000–2009. (Note that

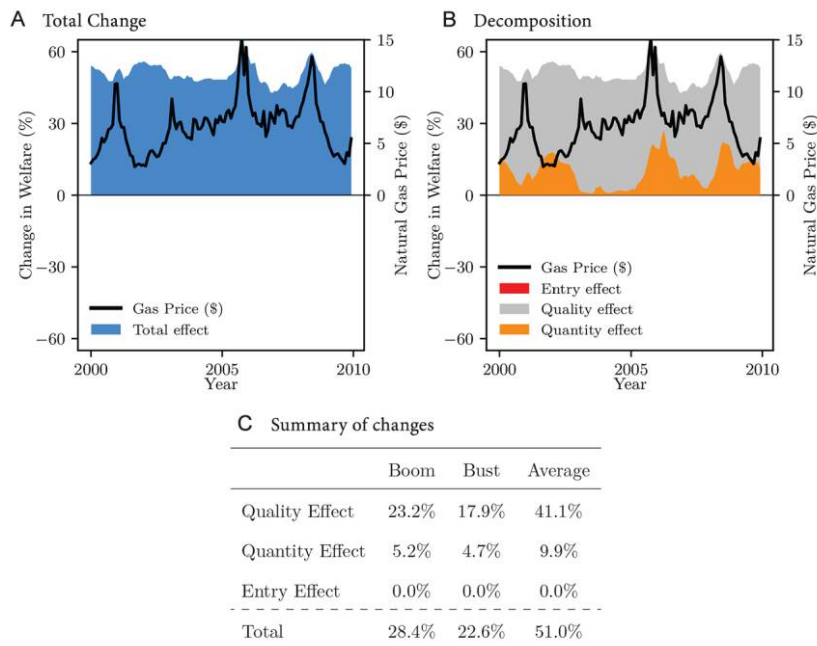


FIG. 8.—Intermediary counterfactual results. *A*, Total change. *B*, Decomposition. Shown is the change in welfare when moving from the market baseline to the intermediary counterfactual. I keep the composition of searching wells fixed to the market benchmark, resulting in an entry effect = 0. The welfare in dollars at the market baseline is 5.0 billion.

here I am using the intermediary as the comparison, so these figures are the change in welfare relative to the total surplus of an intermediary.) This increase in welfare is slightly cyclical: according to panel *C*, the welfare increase in booms is around 28.4% compared with 22.6% in busts.

Panel *B* decomposes the effect of the intermediary. Overall, match quality is higher in all periods, and the total improvement in match quality is 41.1%. The magnitude of the quality effect is slightly cyclical, with the gains in the boom at 23.2%, which is higher than the gains in the bust at 17.9%. The quantity of matches increases in both booms and busts under an intermediary; however, the magnitude of the quantity effect (9.9%) is much lower than the magnitude of the quality effect.

Given the gains from an intermediary, it might seem surprising that there is not currently one in the market. Attempting to explain the non-existence of an intermediary is arguably outside the scope of this paper. That said, as previously mentioned, participants in the industry are attempting to reduce search frictions through recent advances in technology and e-procurement.

### *C. Effects of a Demand-Smoothing Policy*

I now consider the effects of a demand-smoothing policy. There is a long history in the oil and gas industry of policies designed to smooth the disruptive effects of the boom-bust cycle. Between 1954 and 1978, natural gas producer prices were fixed in the United States for interstate trade. Today, many producer incentives, tax credits, and royalty rates are tied to oil and gas prices. For example, the federal marginal well tax credit is available only when the oil prices are below \$18 per barrel. The federal enhanced oil recovery credit is available only if oil prices are below \$28 per barrel.<sup>17</sup> The consequence of these countercyclical policies is to smooth the prices that producers face, increasing oil and gas prices in the busts and decreasing them in the booms.

To understand the effects of these policies on drilling behavior, I consider a counterfactual demand-smoothing policy that results in the natural gas price being held at its long-run average. I am agnostic in the counterfactual about the exact implementation of taxes and subsidies that result in the smoother gas price. The results are depicted in figure 9. Panel *A* shows that the smoothing policy results in large shifts in drilling activity. The shift is somewhat cyclical, with a slight decrease in welfare in the boom (−2.1%) compared with an increase in the bust (17.0%).

Panel *B* illustrates the determinants of the total change. The changes for the quantity effect and the entry effect are straightforward. In terms

<sup>17</sup> Potter et al. (2017) summarize the tax credits that oil and gas producers receive in low-price environments.

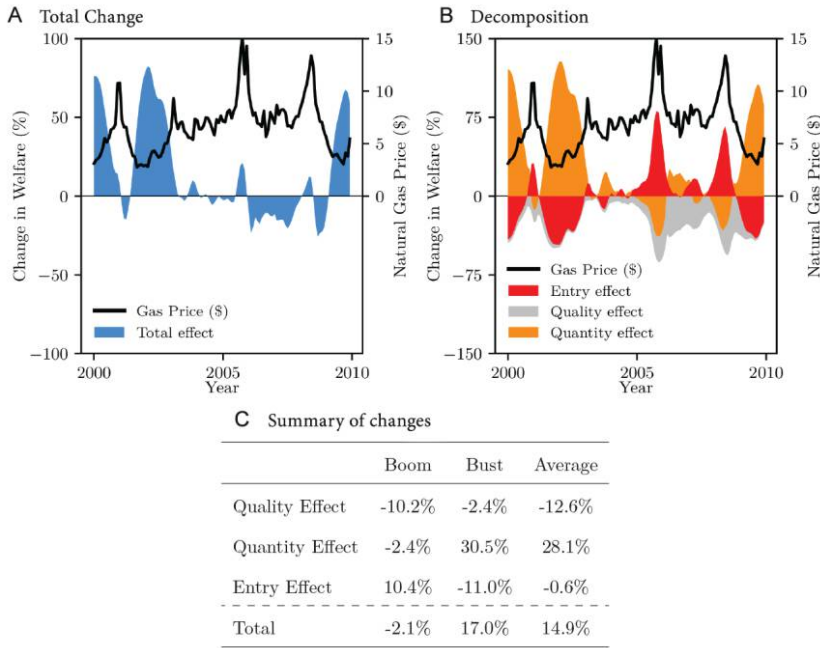


FIG. 9.—Demand-smoothing counterfactual results. *A*, Total change. *B*, Decomposition. Shown is the change in welfare when moving from the market baseline to the demand-smoothing counterfactual. The welfare in dollars at the market baseline is 5.0 billion. The entry effect corresponds to the total change in entry costs, so it will be negative when there is more entry.

of the quality effect, demand smoothing decreases the quality of matches in a boom by  $-10.2\%$  since agents are less selective. Interestingly, match quality also decreases slightly, by  $-2.4\%$ , in the bust: one reason is that demand smoothing results in different compositions of wells entering in these periods.

Given that the counterfactual demand-smoothing policy is extreme—and despite dramatic changes in entry and the quantity of matches—the overall effect of the smoothing policy is modest, at  $14.9\%$ . This suggests that demand-smoothing policies are somewhat ineffective in improving welfare. Collard-Wexler (2013) finds qualitatively similar results for demand smoothing in the ready-to-mix concrete industry: smoothing results in large changes in industry structure but a small improvement in welfare. Although the market structure of the ready-to-mix concrete industry differs from offshore drilling, these results suggest that understanding the industry structure is important for predicting the effects of demand-smoothing policies.

## VII. Conclusion

A large literature has established that firms adjust to booms and busts by reallocating capital and that this process drives aggregate productivity. But much less is known about how firms reallocate capital in practice. Research in this area is needed because the effects of commonly proposed policies such as demand smoothing hinge on the reallocation mechanism.

In this paper I shed light on one such mechanism: matching. I develop a new framework that combines elements of the sequential search literature and firm dynamics literature. The framework incorporates two-sided vertical heterogeneity leading to sorting, as well as a more flexible search technology. I apply the framework to a novel contract dataset in the market for offshore drilling rigs. I argue that booms are associated with a sorting effect, and I provide an identification strategy to separate the sorting effect from changes in the composition of searching projects (demand). I use the framework to quantify the sorting effect, as well as the value of an intermediary and the effects of a demand-smoothing policy.

Overall, this paper presents a unique picture of the inner workings of a decentralized capital market that is affected by booms and busts. My results show that matching is an important reallocation channel in booms and busts for capital markets and that this has significant implications for policy design.

## Data Availability

Code and information about the proprietary data used in this article can be found in Vreugdenhil (2025) in the Harvard Dataverse, <https://doi.org/10.7910/DVN/SRUHG8>.

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