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

Nicholas Vreugdenhil*

June 15, 2023

Abstract

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 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 that demand smoothing policies are ineffective.

*Department of Economics, Arizona State University. Email: nvreugde@asu.edu. Thank you to Robert Porter, Mar Reguant, and Gaston Illanes for their encouragement and advice. I would also like to thank the Editor, Chad Syverson, and four referees, for their thoughtful comments. Thank you to Gaurab Aryal, Esteban Aucejo, Vivek Bhattacharya, Hector Chade, Domenico Ferraro, Igal Hendel, Ken Hendricks, Andreas Kostøl, Nick Kuminoff, Tomas Larroucau, Alvin Murphy, Bill Rogerson, Mark Satterthwaite, and Yuta Toyama for useful comments and suggestions. I thank seminar participants at ASU, Cornell, Duke Fuqua, IIOC, LSE (Management), Microsoft Research, Monash University, NYU, NYU (Stern), Penn State, UCL, and U Maryland AREC. This research was supported by a grant from the Center for the Study of Industrial Organization at Northwestern. I acknowledge IHS and Rigzone for providing data.

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

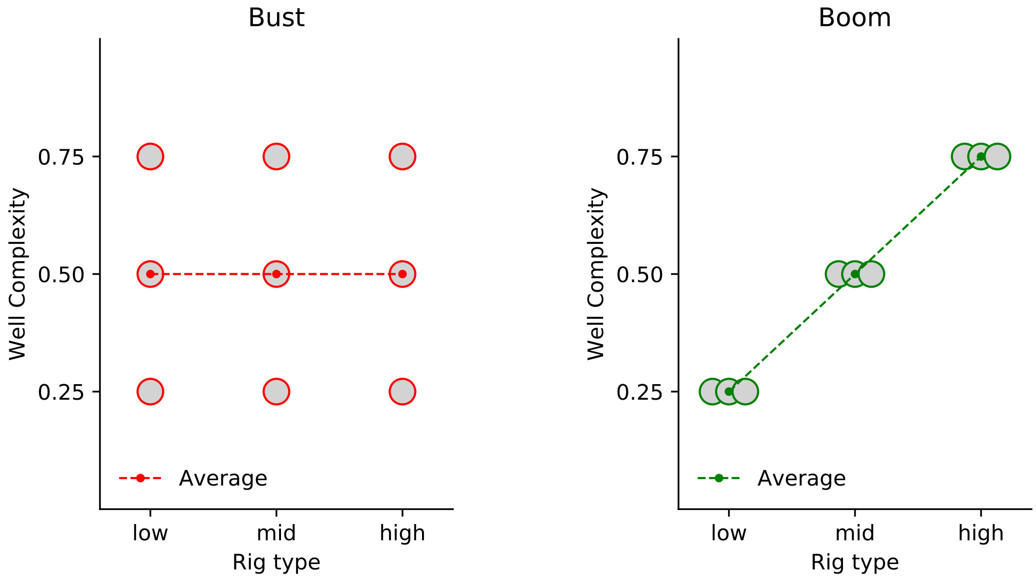
In this paper I focus on markets where output is made by matching heterogeneous producers and heterogeneous factor inputs. Here, booms increase entry rates which can create thick factor markets. This increases the probability of matching, which gives the parties a greater option value of searching for 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 (which are empirical questions), 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 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, as well as quantifying 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

[1] This is largely due to the lack of producer-level data on covariates such as 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).

Figure 1: Illustration of the sorting effect



Note: This figure contains a simple example 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, so long as the match value is supermodular in rig type, there will be higher total output in the boom allocation.

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 pro-cyclical 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 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 search frictions are important in this industry such as the existence of brokers and the emergence of e-procurement. 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.

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 into 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 dollars, over the 2000-2009 period. The sorting effect is cyclical with more efficiency gains in the boom. Decomposing the total effect highlights the main tradeoff in the model: compared to the 'no sorting effect' model, agents in the market tend to drill *less* 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: 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 micro data 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.[2]

Third, previous work typically uses a steady-state analysis to tractably incorporate two-sided

[2]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.

heterogeneity in a search model.[3] 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 such as Kalouptsidi (2014) to cases where short-term contract data are available.

1.1 Related literature

This paper is related to five strands of literature. First it is related to the literature on capital reallocation. Eisfeldt and Shi (2018) provide a review of this literature. Recent work, such as 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) and Dong et al. (2020). This paper advances this literature by - for the first time - providing empirical 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 (for example, Buchholz (2022), Frechette et al. (2019)). A related set of papers study how fluctuations affect long-run firm entry and exit decisions (Kalouptsidi (2014), Collard-Wexler (2013)). 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 pro-cyclical productivity patterns in labor markets e.g. through cyclical job ladders Moscarini and Postel-Vinay (2018),

[3] An exception is Lise and Robin (2017), who model non-stationary distributions of searching agents by assuming Bertrand wage competition.

or alternative mechanisms: Barlevy (2002), Lise and Robin (2017). 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 such as Baccara et al. (2020). Although my framework is quite different to this paper, 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 in Kellogg (2014), Kellogg (2011), Corts and Singh (2004), and Corts (2008). 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 is related directly to lease bids (Porter (1995)).

2 Industry Description and Data

2.1 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 USD in 2010 (Kaiser and Snyder (2013)). I analyze a particular segment of this industry: shallow water (<500ft) 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 an HHI of 1239 for rig owners and an HHI 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 'jackup rigs'. Jackup rigs are barges fitted with long support legs that can be raised or lowered. In order to drill a well a jackup 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 flows 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 drilling a 'well' and drilling a '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 gas price as the driver of exogeneous shocks in this industry.[4] Once a well has been drilled an operator extracts oil and gas at maximum capacity for the lifetime of the well (Anderson et al. (2018)) unless external factors such as hurricanes intervene.

2.2 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 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 and so it is the earliest year 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 on the status of rigs currently drilling and if they are not drilling whether they are available or off the market (for example, 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

[4]Furthermore, in the sample period the oil price is correlated with the natural gas price. I show in Appendix E.2 that simply tracking the natural gas price does not make any difference to the results.

Table 1: Summary statistics for the dataset

Variable	**Units**	**N**	**Mean**	**SD**	**10%**	**90%**
Rig Price - New Contracts	1000s of USD/day	1733	62	35	27	111
Duration - New Contracts	Days	1733	65	76	27	120
Rig Price - Renegotiations	1000s of USD/day	922	52	26	28	81
Duration - Renegotiations	Days	922	68	59	29	126
Value	Millions of USD	2655	8.8	25	0.25	8
Complexity	Index	2655	0.87	0.51	0.34	1.46
Water Depth	Feet	2655	117	80	37	233
Monthly Utilization	% Rigs under contract	360	0.76	0.2	0.49	1.0

Note: Monthly utilization is for each of the 3 types of rig over 120 months.

has slightly more detailed information on whether the contract is new or an extension and so I merge this dataset with the well data.

Contracts follow a simple form: rig owners are paid a fixed price 'dayrate' 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 percent) 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 in 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 (BSEE). The well permit data contain detailed information about the characteristics of each well including depth, location, mud weight, oil and gas produced, etc.

In addition I have lease bid data from which I can estimate participants' beliefs about the value of drilling a well because it is related directly to lease bids (Porter (1995)). To do this I take the highest bid for the corresponding lease.[5] 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.

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 etc that describe the geological environment and transforms them into a one-dimensional index of well complexity.[6] More complex wells (for example, 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 ft to 450 ft. 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. Due to a limited sample size, for estimation I aggregate rigs into three classes by their maximum drilling depth: low ($\leq$ 200 feet), mid ($>$ 200 feet 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.

[5]This is motivated by the fact that offshore lease auctions are common value auctions and as the number of bidders $n \to \infty$ 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 et al. (2010) for evidence that ex-post returns in shallow water OCS auctions are not excessive.

[6]Details on the calculation of the Mechanical Risk Index can be found in Appendix A.2.

2.3 Key features of the industry

The offshore drilling industry is characterized by three key features: (1) sorting patterns; (2) booms and busts driven by oil and gas prices; (3) search frictions.

2.3.1 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.

The observed sorting patterns imply that the match between rig technology and the well complexity matters. Qualitative evidence from the industry provides more detail about how agents make decisions about who 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'*[7]. Note that in Table A-1 in the Appendix I perform a hedonic regression of prices on match characteristics.

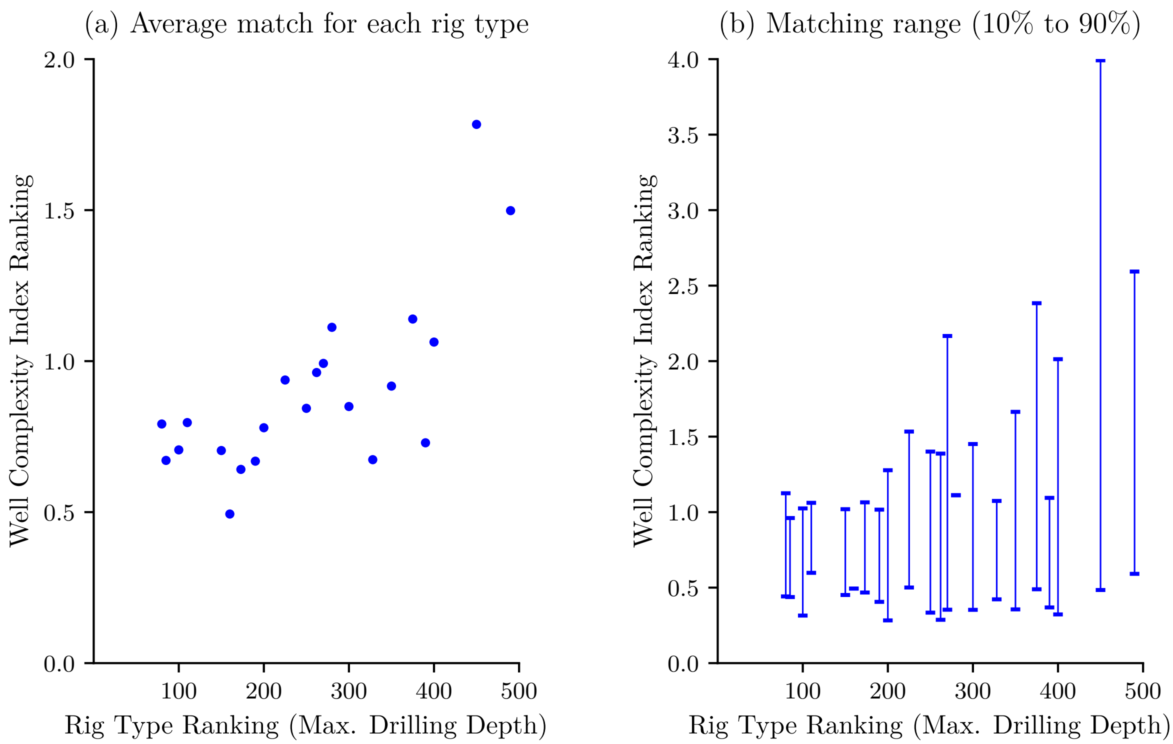
2.3.2 Feature 2: Booms and busts

Figure 3 displays how fluctuations in the 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 thousand per day when gas prices are high but this can fall to $30 thousand per day when gas prices are low. Rig utilization is also cyclical and I document rig utilization patterns in Table A-5 in Appendix D.4.

How booms and busts affect matching Panel (a) of Figure 4 provides evidence consistent with stronger sorting in booms than busts. In the Figure I split the data up into two bins: a

[7] http://www.diamondoffshore.com/offshore-drilling-basics/offshore-rig-basics

Figure 2: Positive assortative matching: higher ranked rigs match with more complex wells



Note: This figure shows the sorting patterns in the data. Rigs are constructed in discrete increments of maximum drilling depth and so each point on the x-axis might correspond to many unique rigs.

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 busts, and more efficient rigs are more likely to be matched to complex wells in booms than busts. I verify in the right panel (which is based on confidence intervals from Table A-4 in the Appendix) 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 Panel (a) of Figure 4. 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

Figure 3: Booms and busts

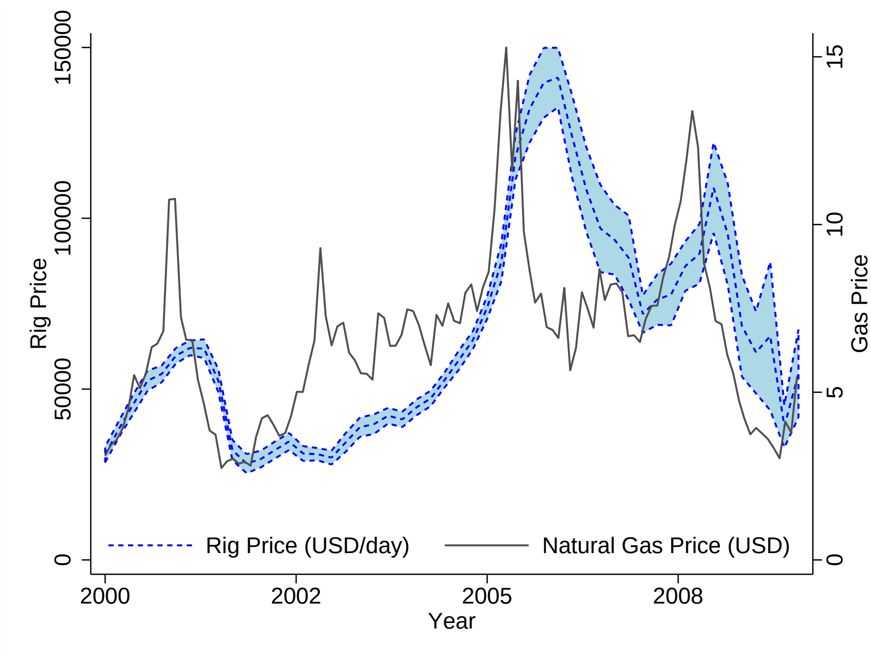
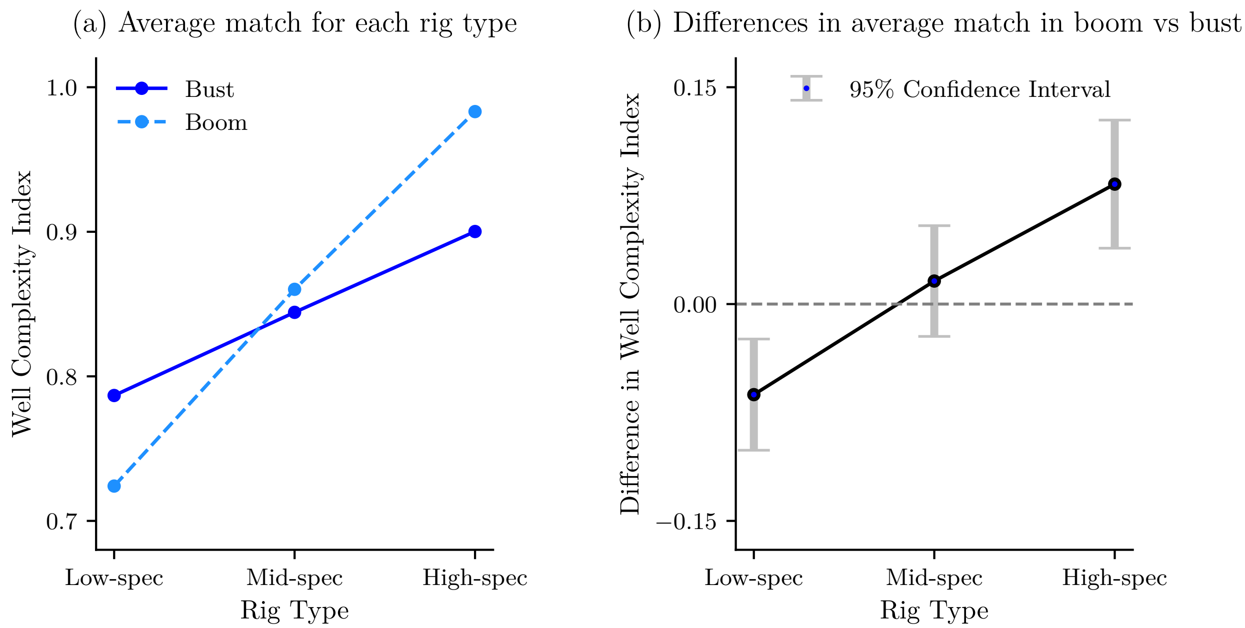


Figure 4: Matching patterns in booms and busts



Note: Panel (a) shows that when a bust turns to a boom, the market features stronger sorting patterns. Panel (b) shows that these differences in matching patterns are statistically significant, using confidence intervals from Table A-4 in the Appendix. Figure A-3 in the Appendix shows the overall composition of matches in booms and busts is relatively similar.

complex wells in booms, as reflected in prices.

2.3.3 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 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). Since my dataset only contains 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 which 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 to help find a match, such as Clarksons, Bassoe Offshore, and Pareto Offshore. As discussed by Brancaccio et al. (2022), 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.[8] 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.

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.[9] 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). Instead, I include a reduced-form matching function that allows for realistic frictions in the search process.

[8] For an early discussion about the potential benefits to e-procurement in the industry see Rothgerber (2002). Raghothamarao (2016) discusses how advances in e-procurement are being used in the oil and gas industry.

[9] For example, which rigs have not yet signed a contract but are in a late stage of negotiations, or if a rig suddenly needs maintenance, or other idiosyncratic heterogeneity.

Table 2: Evidence of price dispersion

	(a) Using aggregated rig types	(b) Using disaggregated rig types
$1 - R^2$	0.37	0.27
$SD(\tilde{p}_{it})$	11	9
$SD(\hat{p}_{it})$	18	18

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

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, and 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-meaned prices on rig characteristics, well characteristics, and contract characteristics. I run the following regression on new contracts:

$$\hat{p}_{it} = \mathbf{X}'\beta + \tilde{p}_{it} \tag{1}$$

Where $\hat{p}_{it}$ are the demeaned prices for match i at month t and $\tilde{p}_{it}$ are residual prices (that is, the residual after regressing prices on the covariates). I use the following covariates $\mathbf{X}$, 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:

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

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 panel (a) 'rig-type' is the aggregated classes (i.e. using {high, mid, low}); in panel (b) 'rig-type' is the disaggregated rig classes (i.e. by maximum drilling depth).

Table 3: Documenting mismatch

	Change in Match Value (Millions USD)		
	Bust	Boom	Difference: Bust vs Boom
Optimal Match vs Empirical Match	0.758	0.594	0.164
T-test	0.002***	0.01***	0.029**

Note: This table previews the 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 USD). 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, where: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Despite controlling for detailed match and contract characteristics Table 2 illustrates there is a high amount of unexplained price variation: 0.37 of total price variation is unexplained when using the aggregated rig types and 0.27 of total price variation is unexplained when using the finer disaggregated rig types. Similarly, the standard deviation of residual prices is 11 thousand USD/day when using aggregated rig types and 9 thousand USD/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 Salz (2022) and Brancaccio et al. (2022).

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.[10]

I report the results from the above procedure in Table 3. In this table I split up 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 \$0.758 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 \$0.594 million. Second, this return is counter-cyclical: the returns to better matching are higher in the bust than the boom by \$0.164 million, which is consistent with the sorting effect.

3 The Model: Sequential Search with Booms and Busts

3.1 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_{quantity} is the quantity of hydrocarbons (oil and gas), and τ 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

[10] 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.

available capital of type y at time t by n_{yt}.

Timing The model is dynamic and one period in the model is one month.[11] To keep notation concise, let the subscript t represent objects at the time t state s_t. The timing in each period is:

1. *Contract extensions.* Existing matches are extended with probability η_{xyt} which is dependent on the state as well as the value of a particular match.

2. *Entry.* The set of potential projects is comprised 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 θ_{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 towards 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 ω_{xyt}. Using the above notation the market tightness can also be formally defined as $\theta_{yt} = n_{yt}/(K_t \cdot \int \omega_{xyt} e_{xt} f_x dx)$.

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 (τ periods). If agents choose to not match then projects exit the market immediately and the capital is available to match in the next period.[12] Note that in the Appendix (Section E.3) I run robustness checks around the assumption of myopic projects and find that relaxing this assumption does not substantially change the results.

[11] I verify in Table A-10 in the Appendix that halving the period length does not affect the results substantially.

[12] 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 if 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 et al. (2020)).

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:

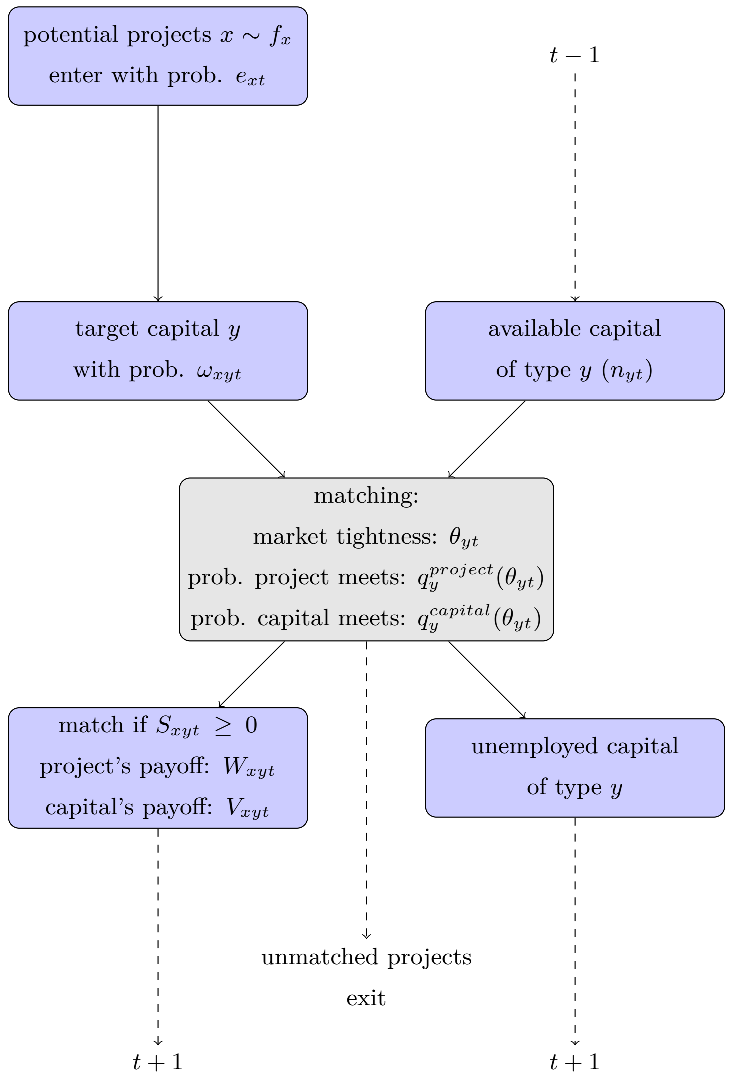
$$v_{xyt,k} = m_{0,y} + m_{1,y} \cdot x_{\text{complexity}} + m_2 \cdot \mathbb{E}_t\left[g_{t+k}\right] x_{\text{quantity}} \tag{2}$$

and 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: $m_{0,y} + m_{1,y} \cdot x_{\text{complexity}}$. Here $m_{0,y}$ and $m_{1,y}$ are coefficients that vary with rig type. This equation captures complementarities 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 ($m_{1,high} > m_{1,mid} > m_{1,low}$) (Becker (1973)).

The second component is $m_2 \cdot \mathbb{E}_t\left[g_{t+k}\right] x_{\text{quantity}}$. 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_{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 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 'depth date') and an additional few days to 'complete' (cap and run in the production tube), which is approximately one month in total and one period in the model. Drill times are relatively similar across wells, e.g. the 0.75 quantile is 26.0 days.

Figure 5: Search and matching within each submarket



Notes: This figure illustrates how capital and projects match. 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 θ_{yt}. Finally, agents choose whether to match based on whether the total surplus of a match is positive ($S_{xyt} \geq 0$).

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 whether to match if agents successfully contact each other. Overall the model focuses on the dynamic tradeoff 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 et al. (2020)) where agents are relatively homogeneous. Due to 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 and 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 sub-market in a similar way to how they would within an individual location in a taxi market, or a port in the bulk shipping market.[13] Within a location distance is assumed to not explicitly factor into rig selection; as previously mentioned and also discussed in Appendix A.3, this seems a reasonable assumption.

3.2 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:

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

The project owner's value of matching W_{xyt} can be decomposed in the following way. For each

[13] In this way, Figure 5 which sets out how meetings take place within a sub-market, can be compared to a similar figure in Buchholz (2022).

period of the τ 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 $q_y^{project}(\theta_{yt})$, amongst other things. For a type-x project denote the (expected) value of searching in the type-y capital submarket as $\pi_{xyt} = q_y^{project}(\theta_{yt}) W_{xyt}$.

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

$$\hat{\pi}_{x_i y_j t} = \pi_{x_i y_j t} - \gamma_1 1 \left[x_i \notin A_{y_j t} \right] + \epsilon_{ijt}^{target} \tag{4}$$

I assume that ϵ_{ijt}^{target} are drawn from an i.i.d. type-1 extreme value distribution with scale parameter $1/\gamma_0$. The interpretation of γ_0 and γ_1 is that they are 'targeting parameters' that index how precisely a project can target capital, and $1[x \notin A_{yt}]$ 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 γ_1) as well as the overall quality of the match: γ_0. The motivation for including the γ_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 $\max\limits_j \hat{\pi}_{x_i y_j t}$ 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:

$$\omega_{xyt} = \frac{n_{yt} \exp\Big(\gamma_0\big[\pi_{xyt} - \gamma_1 1\big[x \notin A_{yt}\big]\big]\Big)}{\sum\limits_{k \in Y} n_{kt} \exp\Big(\gamma_0\big[\pi_{xkt} - \gamma_1 1\big[x \notin A_{kt}\big]\big]\Big)} \tag{5}$$

This search technology is more flexible than the typical assumptions of random search or directed search which are 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 $\gamma_0 \to \infty$, where projects can perfectly identify the best match).

Entry Before making the targeting decision each potential project chooses whether to enter. This decision is: $\max\left\{\sum_{k \in Y} \omega_{xkt}\pi_{xkt} - c + \epsilon_t^{\text{entry}}, \epsilon_t^{\text{no entry}}\right\}$. Here, c is the entry cost and $\epsilon_t^{\text{entry}}$, $\epsilon_t^{\text{no entry}}$ 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, amongst other things. The resulting conditional choice probability that a project enters is:

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

Demand for capital Aggregating up the individual project entry and targeting decisions results 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:

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

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

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 due to different projects entering and different targeting behavior. Given demand for capital, I now turn to the capital owners' problem.

3.3 Capital owners' problem

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

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

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 τ 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:

$$U_{yt} = \underbrace{\int_z \max\left\{V_{zyt}, \beta\mathbb{E}_t U_{y,t+1}\right\} h_{zyt} dz}_{\text{Exp. Value Of A Meeting}} + h_{\emptyset yt} \underbrace{\beta\mathbb{E}_t U_{y,t+1}}_{\text{No Meeting}} \tag{9}$$

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 or not 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:

$$p_{xyt} = \text{argmax}_{p_{xyt}} \left[V_{xyt} - \beta\mathbb{E}_t U_{y,t+1}\right]^\delta \left[W_{xyt}\right]^{1-\delta} \tag{10}$$

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 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 η. These two conditions imply the probability of an extension is $\eta_{xy,t+\tau} = \eta 1\left[S_{xy,t+\tau} \geq 0\right]$.

3.4 Transitions and states

Transitions At the start of each period, rigs are either unemployed or are currently matched. If a rig is currently matched denote τ_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 which do not find a new match become unemployed. At the end of each period, τ_k counts down by 1.

States The detailed industry state in each period is the price in dollars for natural gas g_t, 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 due to 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 these moments that characterize an agent's beliefs about state s_t are:

$$s_t = [g_t, n_{low,t}, n_{mid,t}, n_{high,t}] \tag{11}$$

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 it either enters the period unemployed or if 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 who track the industry to describe the state of the market. Note that while I assume that the agents are relatively small and so 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 $\Sigma = Diag(\sigma_\epsilon, 0, 0, 0)$. In the R_1 matrix, I set the coefficients in the g_t updating rule to zero except for the coefficent 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.

3.5 Equilibrium

Equilibrium is defined as a set of prices p_{xyt}, capital availability $\{n_{yt}\}_{y\in\{low,mid,high\}}$, demand for capital h_{xyt}, targeting weights ω_{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 ω_{xyt}, the 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 choose whether to accept/wait if matched using Equations (8) and (9).
4. Equilibrium prices p_{xyt} determined by Nash bargaining: Equation (10)
5. Updating rule for the distribution of capital $\{n_{yt}\}_{y\in Y}$ according to the description in Section 3.4.
6. Beliefs about the future evolution of states given by an AR(1) process.

4 Estimation and Identification

4.1 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 one period is one month). I calibrate the entry cost c using industry studies that decompose drilling expenditure into entry costs ('pre-spud costs') vs other costs. Using the average total payment to a rig owner as my measure for other drilling costs, I calibrate $c = 1.32$ million USD.[14]

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

$$q_y^{capital}(\theta_{yt}) = \min\{1 - \exp(-a_y/\theta_{yt}), 1/\theta_{yt}\} \tag{12}$$

$$q_y^{project}(\theta_{yt}) = \min\{\theta_{yt}(1 - \exp(-a_y/\theta_{yt})), 1\} \tag{13}$$

This meeting technology can be derived as an approximation to an urn-ball matching function with a large number of agents (see Petrongolo and Pissarides (2001) for a derivation). I also bound the meeting technology to prevent the model 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 ρ_0, ρ_1, ρ_2, and ρ_3, are parameters. I run an OLS regression to recover the parameters $\rho_0, \rho_1, \rho_2, \rho_3$.
- Contract durations are for either 2, 3, or 4 months, and are distributed independently of the other covariates with probability weights (τ_2, τ_3, τ_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 μ, σ need to be estimated. I choose the minimum of the truncated normal as $x_{\text{complexity}} = 0$ and the maximum as $x_{\text{complexity}} = 2.15$.

[14]Specifically, I rely on Hossain (2015) which puts pre-spud 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 dollars.

Table 4: Overview of how the model components are computed

Object	**Parameters**	**Method**
Discount rate, monthly	β	Calibrated: Preliminary
Entry cost	c	Calibrated: Preliminary
State transition beliefs	$R_0, R_1, \sigma_\epsilon$	Estimated: Step 1
Bargaining weight	δ	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	η	Estimated: Step 2
Targeting parameters	γ_0, γ_1	Estimated: Step 2
Meeting Technology	$\{a_y\}_{y \in Y}$	Estimated: Step 2

Note: This table provides an overview of the parameters to be estimated or calibrated.

4.2 Estimation

I estimate the model in two steps, similar to much of the literature on dynamic games (e.g. Bajari et al. (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 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_{yt} 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, Kalouptsidi (2014) uses data on second-hand 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 non-parametrically 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 as well as detailing the forward simulation algorithm.

I then calibrate the bargaining parameter using a similar strategy to Brancaccio et al. (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 non-stochastic 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 which 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.

4.3 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 Panel (a) of Figure 4) could be generated by compositional changes in the set of searching wells, or by the sorting effect. Therefore, amongst other things, I show that acceptance sets and the targeting parameters can be separately identified from the distribution of wells.

Identifying the parameters underlying the 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 δ, 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:

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

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

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

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 just use 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 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 η, 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. As well, 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 the targeting parameters I first discuss how the targeting parameter γ_0 is identified, which 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 also in busts (6 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 γ_0 leading to stronger sorting. Therefore, γ_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 γ_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 (due to a low number of available rigs) but the arrival rate of new projects is also low. Higher values of γ_1 allow for wells to avoid these matches, resulting in fewer rejections and a higher capital utilization.

Identifying the meeting technology parameters In Appendix B.5 I show that the market tightness terms θ_{yt} can be identified given the above parameters. Then, the meeting technology parameters a_y — which relate how θ_{yt} affects the probability of capital matching $q_y^{capital}(\theta_{yt}) = \min\{1 - \exp(-a_y/\theta_{yt}), 1/\theta_{yt}\}$ — 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 (3 moments).

Identifying potential project parameters More potential project draws K_t decrease the market tightness θ_{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 (3 moments), and the variance of utilization for each capital type (3 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 (1 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 and 3 month contract (2 moments).

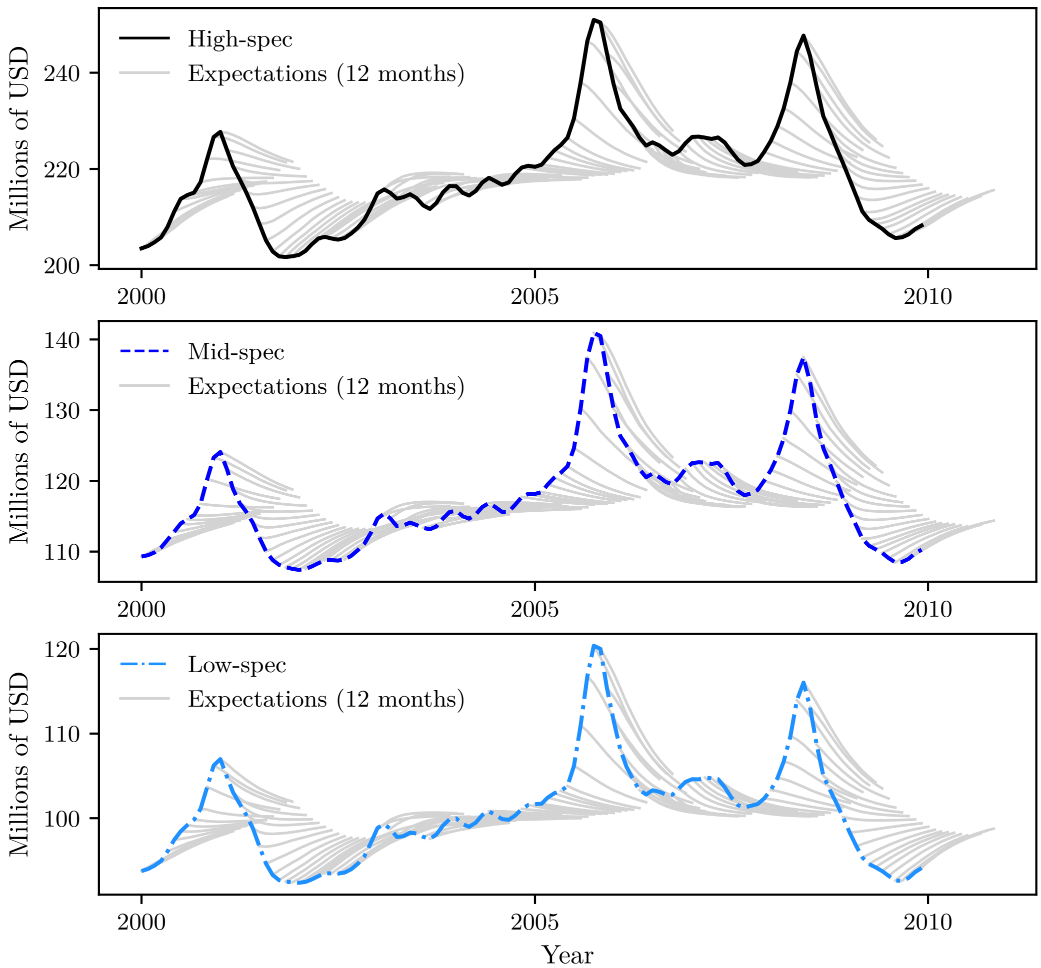
5 Results

Constructing the value of searching U_{yt} The results for the beliefs over the state transitions are (standard errors in brackets and recalling that the states are ordered as $s_t = [g_t, n_{low,t}, n_{mid,t}, n_{high,t}]$):

$$R_0 = \begin{bmatrix} 0.81\ (0.36) \\ 6.95\ (1.86) \\ 4.62\ (2.14) \\ 7.02\ (1.72) \end{bmatrix}, \quad R_1 = \begin{bmatrix} 0.88\ (0.04) & 0 & 0 & 0 \\ -0.41\ (0.15) & 0.71\ (0.08) & 0.07\ (0.09) & -0.03\ (0.08) \\ -0.34\ (0.15) & 0.2\ (0.09) & 0.48\ (0.09) & 0.21\ (0.08) \\ -0.4\ (0.15) & -0.2\ (0.07) & 0.23\ (0.08) & 0.48\ (0.08) \end{bmatrix} \tag{16}$$

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: The rig's value of searching U_{yt}



Notes: Points on the graph are plotted monthly. The gray lines correspond to the 12-month future beliefs of the value of searching.

Figure 6 illustrates the outcome of the forward simulation procedure to obtain U_{yt}. 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, $\mathbb{E}_t U_{t+2}(y)$ etc. 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 over-built, 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 is supermodular. Finally, I find that the value weight m_2 =3.7. Scaling up this per-day figure over a 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 of Appendix D. 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 due to a low value of $m_{1,mid}$. 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 γ_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.[15] 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

[15]Specifically, I choose the state halfway through the sample at January 2005 which is also between a boom and bust.

Table 5: Estimated parameters

Variable	**Symbol**	**Value**	**Symbol**	**Value**
Match Value; Extension	$m_{0,low}$	88.4	$m_{1,low}$	-37.5
		$(74.2, 98.8)$		$(-45.7, -29.3)$
	$m_{0,mid}$	72.6	$m_{1,mid}$	0.7
		$(56.8, 88.9)$		$(0.4, 1.2)$
	$m_{0,high}$	57.2	$m_{1,high}$	40.5
		$(47.4, 67.9)$		$(25.0, 56.6)$
	m_2	3.7	η	0.38
		$(0.7, 10.1)$		$(0.35, 0.4)$
Demand	μ	0.68	τ_2	0.69
		$(0.52, 0.77)$		$(0.65, 0.73)$
	σ	0.72	τ_3	0.2
		$(0.57, 0.95)$		$(0.17, 0.23)$
	ρ_0	0.031	ρ_1	0.037
		$(0.015, 0.047)$		$(0.001, 0.073)$
	ρ_2	-0.024	ρ_3	0.0028
		$(-0.044, -0.004)$		$(0.0003, 0.0053)$
Entry Cost; Bargaining Parameter	c	\$1.32 Million	δ	0.37
		n.a.		n.a.
Potential Project Draws	k_0	22.9	k_1	8.0
		$(11.1, 31.0)$		$(6.1, 11.3)$
Meeting Technology	a_{low}	0.44	a_{mid}	0.57
		$(0.31, 0.62)$		$(0.41, 0.71)$
	a_{high}	16.5		
		$(8.02, 25.12)$		
Targeting Parameter	γ_0	0.71	γ_1	1.43
		$(0.26, 1.11)$		$(0.51, 2.25)$

Note: All parameters are estimated using the simulated method of moments, except for estimates for $\rho_0, \rho_1, \rho_2, \rho_3$ which are computed using the OLS regression of $x_{\text{quantity}} = \rho_0 + \rho_1 x_{\text{complexity}} + \rho_2 x^2_{\text{complexity}} + \rho_3 x^3_{\text{complexity}}$. Confidence intervals (95%) in brackets. An *n.a.* term in the confidence interval denotes a calibrated value. The confidence intervals are computed using 200 bootstrap replications, except for estimates for $\rho_0, \rho_1, \rho_2, \rho_3$ which are computed using the standard errors from the OLS regression.

data is closer to random search than directed search. In terms of the targeting parameter γ_1 I find that it is positive but relatively small.

For the matching efficiency parameters, the values of a_{low}, a_{mid} indicate that matching in the corresponding submarkets is not perfectly efficient. In contrast, the value of a_{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 in Appendix D 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.

6 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 as well as to assess potential policies to improve matching. Two counterfactuals are centered around quantifying the economic forces at work in the market. I first quantify the extent to which the sorting effect improves allocations. Second, after accounting for the presence of the sorting effect, I then quantify the remaining misallocation from search frictions. I do this through the lens of an intermediary, which is also interesting in its own right due to the rise of e-procurement in the industry. Finally, given that an intermediary which can greatly reduce search frictions may not be feasible, I instead keep the baseline search technology and test a common policy response to business cycles: demand smoothing.

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 $T = \{2000 : 1, ..., 2009 : 12\}$, the total welfare is:

$$\sum_{t \in T} \left(\left\{ \text{Total value of projects by } Y \text{ at } t \right\} - \left\{ \#\text{projects entered at } t \right\} * c - OPEX \right)$$

where OPEX is the total operating expenses of the rigs, which I set to be \$32 thousand per day per rig.[16] I recompute the value functions in the counterfactuals where necessary, as well

[16]This figure comes from Kaiser and Snyder (2013), as the expenses for an operating Jackup rig in the US Gulf

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 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.

6.1 Quantifying the sorting effect

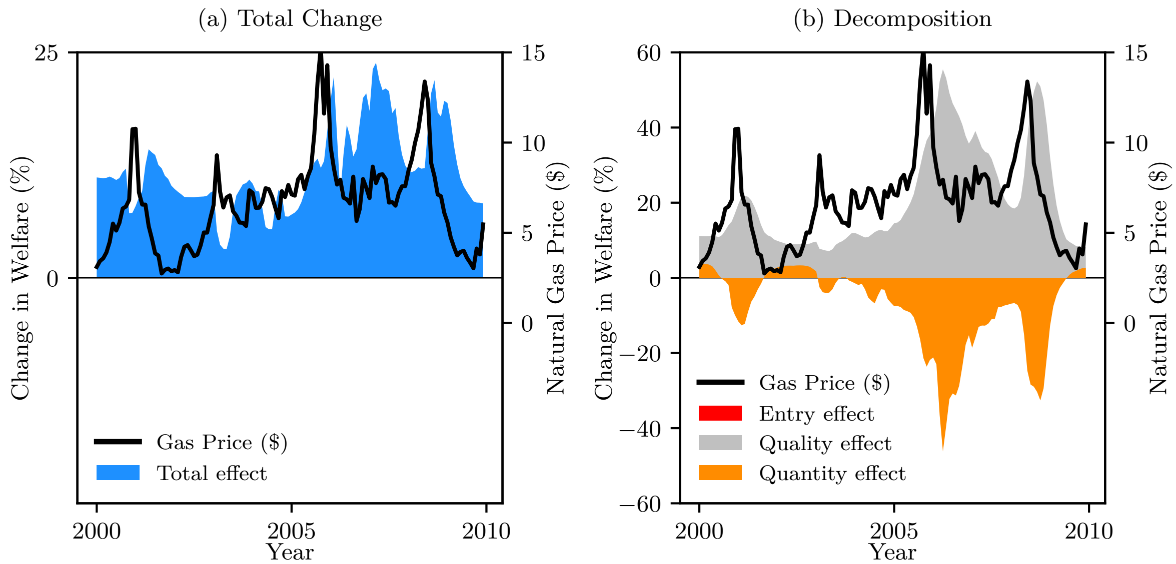
I first quantify how stronger sorting in booms increases welfare. Recall that the sorting effect arises because the option value of searching increases in a boom compared to a bust, and therefore agents are more selective in matching in booms than busts. Consequently, to quantify the sorting effect, 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 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 less matches (which by itself decreases welfare by -8.2%), but the remaining matches are of higher quality because

of Mexico 2010-2011 as reported in the Hercules Offshore annual report. Hercules Offshore is a firm that owns and leases out drilling rigs. Operating expenses include, for example, routine rig maintenance.

Figure 7: No sorting counterfactual results



(c) Summary of changes

	Boom	Bust	Average
Quality Effect	15.4%	4.8%	20.2%
Quantity Effect	-8.1%	-0.1%	-8.2%
Entry Effect	0.0%	0.0%	0.0%
Total	7.3%	4.7%	12.0%

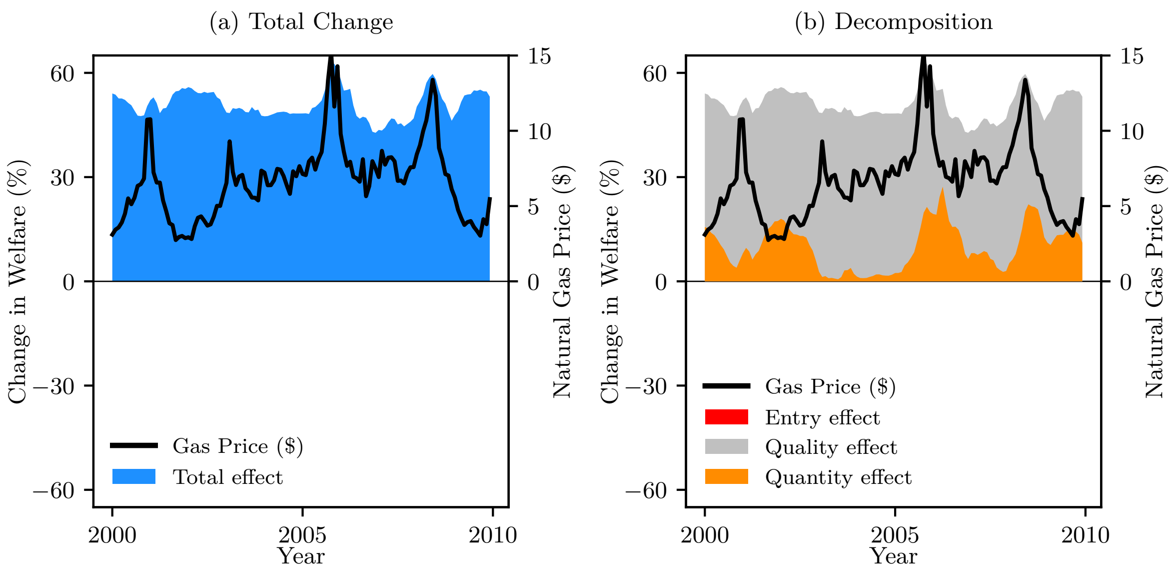
Note: This figure shows the change in welfare when moving from the 'no sorting' counterfactual to the market baseline. I keep the composition of searching wells fixed to the market benchmark resulting in an entry effect = 0. The welfare in dollars at the market baseline is 5.0 billion.

agents are more selective (which increases welfare by 20.2%). Overall, the match quality effect dominates, which results in a net increase in welfare.

6.2 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'

Figure 8: Intermediary counterfactual results



(c) Summary of changes

	Boom	Bust	Average
Quality Effect	23.2%	17.9%	41.1%
Quantity Effect	5.2%	4.7%	9.9%
Entry Effect	0.0%	0.0%	0.0%
Total	28.4%	22.6%	51.0%

Note: This figure shows 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.

which matches the set of entered wells to a submarket of available rig types in each period. The algorithm is 'greedy' because it only considers 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 due to 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 and so 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 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% versus 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 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.

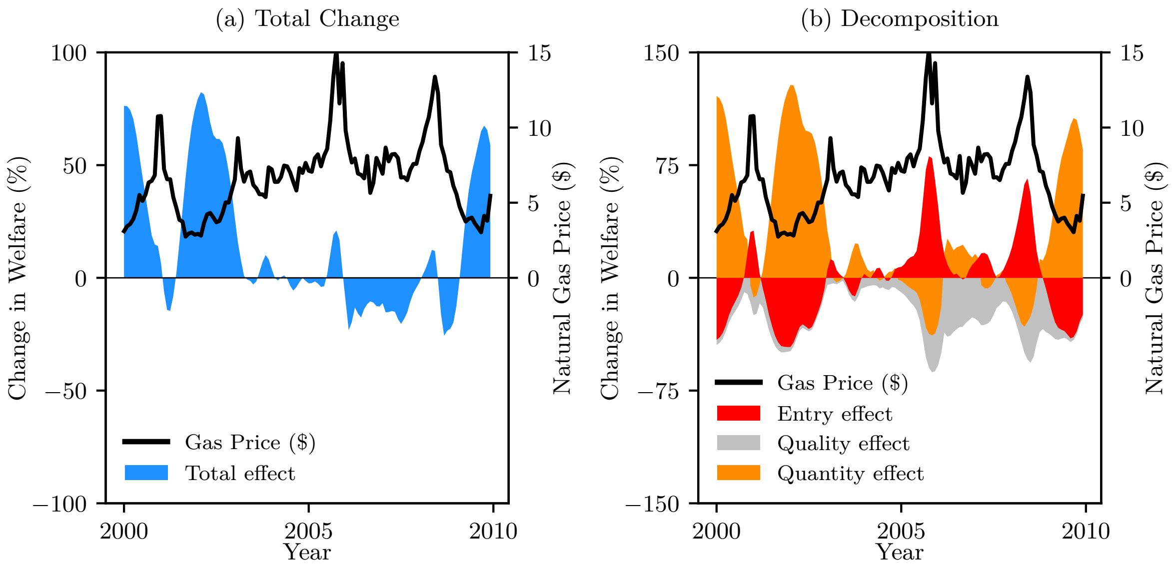
Given the gains from an intermediary, it might seem surprising that there is not currently one in the market. Attempting to explain the non-existence of an intermediary is arguably outside the scope of this paper. That said, as previously mentioned, participants in the industry are attempting to reduce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

6.3 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 out 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 only available when the oil prices is below $18 per barrel. The Federal Enhanced Oil Recovery Credit is only available if oil prices are below $28 per barrel.[17] The consequence of these counter-cyclical policies is to 'smooth' out the prices that producers face, increasing oil and gas prices in the bust and decreasing them in the booms.

[17] Potter et al. (2017) summarizes the tax credits oil and gas producers receive in low-price environments.

Figure 9: Demand smoothing counterfactual results



(c) Summary of changes

	Boom	Bust	Average
Quality Effect	-10.2%	-2.4%	-12.6%
Quantity Effect	-2.4%	30.5%	28.1%
Entry Effect	10.4%	-11.0%	-0.6%
Total	-2.1%	17.0%	14.9%

Note: This figure shows 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 and so will be negative when there is more entry.

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%) versus 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 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 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.

7 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, and 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.

References

Anderson, S. T., Kellogg, R. and Salant, S. W. (2018), 'Hotelling under Pressure', *Journal of Political Economy* **126**(3), 984–1026.

Baccara, M., Lee, S. and Yariv, L. (2020), 'Optimal dynamic matching', *Theoretical Economics* **15**, 1221–1278.

Bajari, P., Benkard, C. L. and Levin, J. (2007), 'Estimating Dynamic Models of Imperfect Competition', *Econometrica* **75**(5), 1331–1370.

Barlevy, G. (2002), 'The Sullying Effect of Recessions', *The Review of Economic Studies* **69**(1), 65–69.

Becker, G. S. (1973), 'A Theory of Marriage: Part I', *Journal of Political Economy* **81**(4), 813–846.

Brancaccio, G., Kalouptsidi, M. and Papageorgiou, T. (2020), 'Geography, Transportation, and Endogenous Trade Costs', *Econometrica* **88**, 657–691.

Brancaccio, G., Kalouptsidi, M., Papageorgiou, T. and Rosaia, N. (2022), 'Search Frictions and Efficiency in Decentralized Transport Markets', *Working Paper* .

Buchholz, N. (2022), 'Spatial Equilibrium, Search Frictions, and Dynamic Efficiency in the Taxi Industry', *Review of Economic Studies* **89**, 556–591.

Collard-Wexler, A. (2013), 'Demand Fluctuations in the Ready-Mix Concrete Industry', *Econometrica* **81**(3), 1003–1037.

Collard-Wexler, A. and De Loecker, J. (2015), 'Reallocation and Technology: Evidence from the US Steel Industry', *American Economic Review* **105**(1), 131–171.

Corts, K. S. (2008), 'Stacking the Deck: Idling and Reactivation of Capacity in Offshore Drilling', *Journal of Economics And Management Strategy* **17**(2), 271–294.

Corts, K. S. and Singh, J. (2004), 'The Effect of Repeated Interaction on Contract Choice: Evidence from Offshore Drilling', *The Journal of Law, Economics, and Organization* **20**(1), 230–260.

Dong, F., Wang, P. and Wen, Y. (2020), 'A Search-Based Neoclassical Model of Capital Reallocation', *European Economic Review* **128**.

Eisfeldt, A. and Shi, Y. (2018), 'Capital Reallocation', *Annual Review of Financial Economics* **10**.

Frechette, G., Lizzeri, A. and Salz, T. (2019), 'Frictions in a Competitive Regulated Market: Evidence from Taxis', *American Economic Review* **109**(8), 2954–2992.

Gavazza, A. (2016), 'An Empirical Equilibrium Model of a Decentralized Asset Market', *Econometrica* **84**(5), 1755–1798.

Haile, P., Hendricks, K. and Porter, R. (2010), 'Recent U.S. Offshore Oil and Gas Lease Bidding: A Progress Report', *International Journal of Industrial Organization* **28**(4), 390 – 396.

Hendricks, K. and Kovenock, D. (1989), 'Asymmetric Information, Information Externalities, and Efficiency: The Case of Oil Exploration', *The RAND Journal of Economics* **20**(2), 164–182.

Hendricks, K. and Porter, R. H. (1996), 'The Timing and Incidence of Exploratory Drilling on Offshore Wildcat Tracts', *The American Economic Review* **86**(3), 388–407.

Herrnstadt, E. M., Kellogg, R. and Lewis, E. (2020), 'The Economics of Time-Limited Development Options: The Case of Oil and Gas Leases', *NBER Working Paper* (No. 27165).

Hossain, M. E. (2015), 'Drilling Cost Estimation for Hydrocarbon Wells', *Journal of Sustainable Energy Engineering* **3**(1).

Ifrach, B. and Weintraub, G. Y. (2017), 'A Framework for Dynamic Oligopoly in Concentrated Industries', *The Review of Economic Studies* **84**(3), 1106–1150.

Kaiser, M. and Snyder, B. (2013), *The Offshore Drilling Industry and Rig Construction in the Gulf of Mexico*, Springer-Verlag, London.

Kalouptsidi, M. (2014), 'Time to Build and Fluctuations in Bulk Shipping', *American Economic Review* **104**(2), 564–608.

Kellogg, R. (2011), 'Learning by Drilling: Interfirm Learning and Relationship Persistence in the Texas Oilpatch', *The Quarterly Journal of Economics* **126**(4), 1961–2004.

Kellogg, R. (2014), 'The Effect of Uncertainty on Investment: Evidence from Texas Oil Drilling', *American Economic Review* **104**(6), 1698–1734.

Lanteri, A. (2018), 'The Market for Used Capital: Endogenous Irreversibility and Reallocation over the Business Cycle', *American Economic Review* **108**(9), 2383–2419.

Lentz, R. and Moen, E. R. (2017), 'Competitive or Random Search?', *Working Paper* .

Lise, J. and Robin, J.-M. (2017), 'The Macrodynamics of Sorting between Workers and Firms', *American Economic Review* **107**(4), 1104–1135.

Moscarini, G. and Postel-Vinay, F. (2018), 'The cyclical job ladder', *Annual Review of Economics* **10**(1), 165–188.

Ottonello, P. (2018), 'Capital Unemployment', *Working Paper* .

Petrongolo, B. and Pissarides, C. (2001), 'Looking into the Black Box: A Survey of the Matching Function', *Journal of Economic Literature* **39**, 390–431.

Porter, R. H. (1995), 'The Role of Information in U.S. Offshore Oil and Gas Lease Auctions', *Econometrica* **63**(1), 1–27.

Potter, K., Shirley, D., Manos, I. and Muraoka, K. (2017), 'Tax Credits and Incentives for Oil and Gas Producers in a Low-Price Environment', *Journal of Multistate Taxation and Incentives* **27**(2).

Raghothamarao, V. (2016), 'Strategic Supply Chain and Procurement Best Practices in Oil and Gas', *Supply and Demand Chain Executive Magazine* .

Rothgerber, U. (2002), 'E-Procurement Still Evolving For E and P Industry', *Oil and Gas Journal* **100**(16).

Salz, T. (2022), 'Intermediation and Competition in Search Markets: An Empirical Case Study', *Journal of Political Economy* **130**(2).