Platform Mergers in Search Markets: An Application in the U.S. Used Heavy Truck Market *

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The latest draft is available here

Abstract

This paper analyzes the welfare effects of lowering the costs to buyers of searching and multihoming in a setting with multiple two-sided platforms. The analysis is motivated by observed changes following the 2017 acquisition of Iron Planet, which is an online auction marketplace for used heavy equipment by Ritchie Brothers Auctioneers, which operates the largest offline auction marketplace. As is quite common after platform mergers, RBA maintained both platforms but made it easier for buyers of equipment to search across the platforms (multihoming), which has the potential to render the allocation of equipment more efficient, benefitting both buyers and sellers. These efficiencies could offset the market power created by the merger. This paper uses pre- and post-merger transaction data to estimate a new model of search and auction entry by buyers and quantify the increase in welfare effects of the observed changes. Depending on the specification, the proportion of multihoming buyers increases substantially (by 50% in the baseline specification), and the total surplus can increase by more than 8%, although heterogeneity exists in the welfare impact on different market participants. This paper also considers several additional counterfactuals involving changes in commission and changes in equipment allocation across the marketplaces.

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1 Introduction

Transaction platforms, especially digital ones, that link buyers and sellers play an increasingly important role in the economy. As of August 2019, digital platforms exceed more than four trillion dollars in market capitalization. When different goods are listed for sale on different platforms, multihoming by buyers (i.e., searching multiple marketplaces) can raise the efficiency of the ultimate allocation. One efficiency that might be considered when analyzing a merger of platforms is that the merged firm could facilitate multihoming by developing cross-platform search tools after the merger. This type of cognizable efficiency could potentially offset any market power created by the merger.[1]

The partial platform integration, in which both platforms remain distinct but cross-platform searching is facilitated, is a common outcome of platform mergers. For example, after acquiring the resale ticket platform StubHub, eBay reports the listings available on StubHub when a buyer searches on eBay. Similarly, after their acquisition by CoStar Group, Apartment.com and ApartmentFinder.com use a cross-search mechanism to help users search for apartments on both platforms.

While two competing platforms may be reluctant to facilitate multihoming since it might intensify competition for single-homing sellers (Caillaud and Jullien [2003], Armstrong [2006], Armstrong and Wright [2007]), a merged platform might seek to encourage multihoming to increase the surplus the platforms generate, which it may have a greater ability to extract. In this paper, I quantify several welfare effects of this type of integration by analyzing the effects of the 2017 acquisition of Iron Planet (IP), an entirely online auction marketplace for used heavy equipment, by Ritchie Brothers Auctioneers (RBA), the largest traditional auction marketplace that operated in 31 physical auction sites across the United States. The transaction was subject to a second request investigation by the U.S. Department of Justice's Antitrust Division (DOJ), but was not ultimately challenged.

I use data of sales of used truck tractors from both platforms before and after the acquisition to estimate a model of buyers' choices of whether to multihome, how many listings to search and which auction to enter to quantify how buyer behavior changed after the acquisition and the effects of this change on the surplus of different market participants. I find that multihoming by buyers substantially increased, and there was some increase in the average number of searches. Despite the small increase in commission, I find that the changes in buyer behavior increased the combined welfare of buyers and sellers and the platform's revenues. This finding is consistent with the DOJ's decision. As I will discuss, the platforms accounted for a relatively small share of the overall used truck market, even though they accounted for up to 60% of the truck auction market. Therefore, the fact that

[1] The Supreme Court decision regarding *American Express vs. Ohio* indicates it is important to evaluate welfare effects on both sides of a transaction platform.

the merger created only limited market power in this setting is unsurprising. However, the welfare benefits due to the lower search costs are substantial and suggesting that these types of efficiencies should also be seriously considered in settings in which a merger may create more market power.

This paper makes two contributions. The first contribution is providing the first evaluation of a change in platform design that is commonly associated with platform mergers in which both platforms exist post-merger. Most empirical existing platform literature focuses on traditional media markets (Rysman [2004], Argentesi and Filistrucchi [2007] and Jeziorski [2014]) and the mechanisms used on one online platform (Arnosti et al. [2014], Fradkin [2017] and Horton [2019]). The trade-off between changes in search costs and other policy changes has not been clearly discussed while considering the competition and mergers between platforms.

To the best of my knowledge, the only study that also empirically analyzes the effects of online platform mergers is **?**. These authors consider the acquisition in pet-sitting services in which one platform was shut down post-merger and provide a reduced-form analysis of how platform use changes. In contrast, I estimate a structural model of buyer search to evaluate the welfare effects of changes that facilitated search across platforms.

The second contribution is to develop and to estimate a new buyer search model that combines choices regarding whether to multihome, how many truck auctions to search, and which auction to enter. This model, combining search with endogenous entry, can be applied to other transaction platforms where allows products to be vertically differentiated and sold by auction.

My model works in the following way. Given their private draws of marginal search costs for additional search and fixed search costs to multihome, buyers decide whether to search both platforms and how many auctions to search. In the used truck auction market, the marginal search costs include an effort to search for trucks online, consult with sales representatives, etc., while the fixed costs of multihoming include the time to learn two systems, register two accounts to monitor trucks, etc. Searching allows buyers to discover individual trucks' characteristics and their private values. Then, buyers simultaneously decide which searched auctions to enter. Finally, buyers bid in the entered auctions. I develop a numerical method to solve the equilibrium in the auction entry stage. I consider two variants of the model. In one variant, all buyers have the same preference for quality, and all single-homing buyers follow the same random entry rule when choosing platforms, and in the other, buyers can have two different preferences for quality and can follow different rules while choosing platforms when single homing. The two-type model is motivated by the fact that buyers who are trucking companies can operate locally or interstate.

The model provides several predictions regarding the market outcome under certain assumptions. It predicts that lower search costs will encourage buyers to perform more searches across the two platforms. Then, buyers can access more information about the trucks before making their auction entry choices. High-quality trucks can be sold to a set of buyers with higher willingness to pay (WTP). Meanwhile, the lower search costs provide buyers access to more trucks across the platforms, resulting in the allocation results of one platform more sensitive to the quality of trucks available on the other platform. These predictions are consistent with the patterns in the pre- and post-merger transaction data.

I estimate a parametric version of the model, although I can prove the non-parametric identification in some cases when there is enough variation in the sets of available trucks across markets. I estimate the model using a two-step procedure. In the first step, I adopt a Nested Fixed Point Algorithm to estimate the distribution of WTP and equilibrium search choices. In the second step, I estimate the bounds of the distribution of search costs by calculating the benefits of different search choices and using the equilibrium conditions in the model.

The estimation results show that buyers' WTP depends on the observed quality of trucks (which I reduce to a single index) and that buyers discount the quality of trucks sold online. Regarding the distribution of search costs, the marginal search cost per search and the fixed search cost of performing multihoming both significantly decrease after the merger. Although buyers' searches are strategic substitutes, the lower search costs still encourage buyers to search for more trucks on average (in the model with one type of buyers, the average number of searches increases from 5.8 to 6.3). Following the merger, more than 50% of buyers shifting from single-homing to multihoming in the baseline model. The increase in the search frequency of buyers with a high-quality preference choosing single-homing offline is more significant than that of buyers with a low-quality preference.

Based on the estimation results, I quantify the welfare effects of the changes associated with the merger. I focus on the following three types of changes: search costs, commission fees and supply side (numbers and types of trucks available on each platform). I capture the partial effect of different elements in different counterfactuals by controlling for other changes.

In the first and main counterfactual, I look at the effect of changes in search costs, keeping the commission rates and supply-side fixed. This comparison shows that the merger can increase the total surplus by more than 8%, among which 6% comes from better matches, and the rest comes from saving in search costs. The total surplus of the buyers and sellers from trading significantly increases. However, the split of the trading surplus among the participants is uneven. While sellers with high-quality trucks can always benefit, it is more ambiguous for other groups. For example, buyers' trading surplus is lower post-merger, considering the fiercer competition among buyers. The cost decomposition shows there is efficiency gain from lowering the cost to multihome alone.

The second counterfactual discusses how the changes in commission structures can impact social welfare. When there is no reserve price, the observed change in commission rate transfers a share of the surplus from sellers to platforms, but the total surplus is the same if we treat the supply side exogenous. Suppose the platforms use auctions with reserve prices and set significantly higher commission rates. In that case, buyers may be discouraged from conducting more searches because buyers' expected payoffs from more searches become lower. However, based on my calculation, it requires a more significant increase in commission rate to offset the efficiency gain from lower search costs in this merger, given the supply side fixed.

Finally, I analyze the additional welfare effect from a possible change on the supply side following the merger. The way to construct the possible change is motivated by the data: post-merger, high-quality goods are more likely to be listed offline, and low-quality goods are more likely to be listed online. I consider a model of two types of buyers where the interstate companies have a higher estimated quality preference and are assumed to choose the offline platform if they conduct single-homing. The results show that this change can generate additional benefits: specifically, with the post-merger search costs, it can increase the total trading surplus by about 2%. This is because it can help buyers with different search strategies to target the goods they prefer more easily.

The reader should be aware of the limitation of my analysis. This paper focuses on buyers' behavior while considering sellers and platform decisions exogeneous because of limited data of other auction platforms and the computation burden. I analyze the changes in sellers and platforms in the counterfactual part. Therefore, the indirect network effect in this platform market cannot be properly analyzed. I discuss the plan to endogenize sellers' platform entry and incorporate indirect network effect in the paper. Additionally, actual buyers' search data are not publicly available; thus, the distribution of search costs is estimated based on the observed transaction and bidding data.

Related Literature. This paper builds upon the literature concerning multi-sided platforms, search, and auction.

Most theoretical papers (Caillaud and Jullien [2003], Rochet and Tirole [2003], Rochet and Tirole [2006], Armstrong [2006], and Weyl [2010]) have focused on prices when discussing mergers and assume that no search costs exist in the market. These papers construct models to analyze the competition between multi-sided platforms. They focus on the number of users on two sides and the indirect network effect rather than the composition of users and matching distortion between users on different sides. Bardey and Rochet [2010] is among the very few papers that consider vertically differentiated users in the health insurance market.

In addition to the literature concerning traditional media markets, recently, more studies have focused on online platforms', Arnosti et al. [2014] mention the potential congestion in the matching market with costly screening and uncertain availability. Fradkin [2017] discusses transaction costs and potential congestion in the Airbnb market. As a typical format of online platforms, online auction markets are analyzed in several papers. Krasnokutskaya et al. [2020] study the role of an online procurement market. These authors develop a way to estimate primitives when unobserved seller heterogeneity exists. Bodoh-Creed et al. [2016] discuss efficiency in decentralized auction platforms. Marra et al. [2019] show how the careful design of a commission structure can improve welfare in a wine auction platform with network effect exits. However, most of the analysis focuses on mechanism design within one online platform.

The search model used in this paper is related to Allen et al. [2014] and Salz [2020]. Allen et al. [2014] point out the importance of considering the search costs in the market when analyzing the merger effect in the Canadian Mortgage industry. Salz [2020] discusses the function of intermediation in New York City's trade waste market. Both papers use a non-sequential search model (De los Santos et al. [2012]) and introduce a competition stage to determine the price rather than posted price setting (Hortaçsu and Syverson [2004]). In their papers, with more searches, consumers can access more lenders/carters (corresponding to sellers in this paper), and lenders/carters compete in the auctions by offering the lowest prices to consumers. Differently, in my model, by searching for more goods, buyers can observe the quality and private values of these goods. Based on this information, buyers make their auction entry choices and compete in the auctions.

Therefore, my model includes a buyers' endogenous auction entry stage. Levin and Smith [1994] and Athey et al. [2011] study the endogenous auction entry model, where Athey et al. [2011] compare the sealed bid and open formats in the U.S. Forest Service timber auctions. They assume bidders have information about their private value after entering the auctions, so bidders are not selective. Different from these papers, my model involves buyers choosing which auction to enter, assuming that they know their values of the goods being sold in each auction that they search.[2]

This paper proceeds as follows. Section 2 introduces the market and data. I illustrate several descriptive findings in the data. Section 3 describes the game played by buyers and discusses the economics of search choices. Sections 4 and 5 describe the identification and estimation strategies. Section 6 presents the structural estimates. Section 7 is the coun-

[2]There is an extensive literature on entry into single auctions under different information assumptions. My model assumes that buyers know their values, as in Samuelson [1985], but more importantly, they are choosing which, of several auctions, to enter rather than considering an "in/out" entry choice into a single auction.

terfactual part and shows the welfare analysis of different policy changes from the merger. Section 8 talks about the plan to relax the assumption of exogenous sellers. Section 9 concludes the paper.

2 Market and Data

This section first provides an overview of the market and acquisition. Then, I discuss the data used in this paper and summarize some interesting findings observed in the data.

2.1 Market for Used Truck Tractors

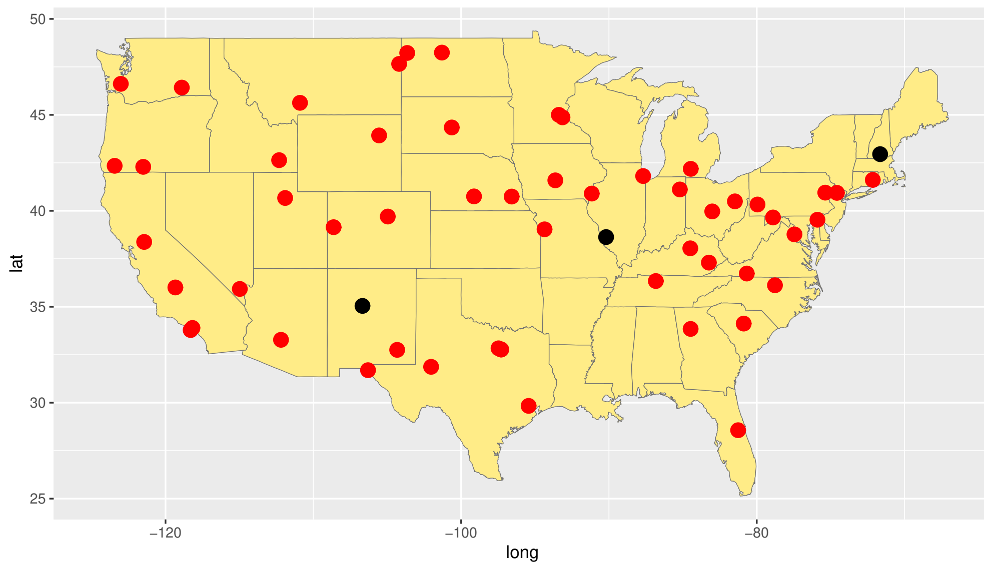
In this paper, I study two platforms, i.e., RBA and IP, on which used truck tractors and many other types of heavy equipment are sold through auctions.

2.1.1 Channels for Used Truck Tractor Sales

Each month, approximately 20,000 used heavy trucks are sold in the U.S. Among these sales, auctions account for about 10%-15% of used heavy trucks in the U.S. each year. Although the auction channel's market share is less than that of some other intermediaries, such as retailers, it allows sellers to sell "as is, where is," namely, sellers need less certification to sell their trucks via auctions than via other channels. Therefore, the auction market is irreplaceable, and on average, the used trucks sold through auctions are older or have higher mileage. Many different body-style trucks exist, and different trucks are used for different purposes. Truck tractors are among the most popular body-style of heavy trucks (see Figure A1). The owners of these trucks are usually transportation trucking companies, operating locally or interstate. The inventory of trucks of local trucking companies is much smaller than that of interstate companies. To operate interstate, companies need to register their trucks under an interstate registration plan.[3]

[3]The International Registration Plan (the Plan) is a registration reciprocity agreement among the states of the United States and provinces of Canada providing payment for license fees based on the total distance operated in all jurisdictions. https://www.irponline.org/page/ThePlan The trucking companies under this Plan usually operate interstate.

Figure 1: Auction Locations of RBA



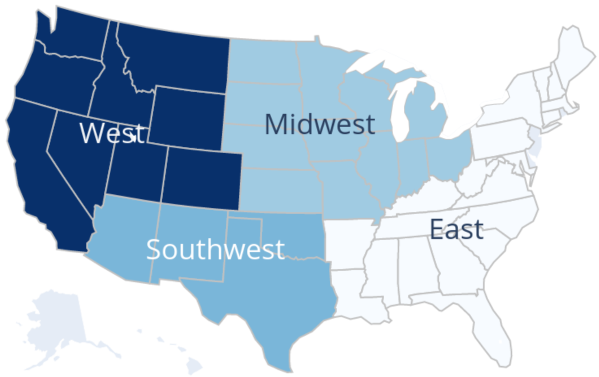
Notes: the black points represent the auction sites that closed after the merger.

2.1.2 Ritchie Bros. Auctioneers

RBA is a primary auction platform that sells heavy industrial equipment through onsite auctions. It has 31 physical auction sites located nationwide (Figure 1), and most locations are concentrated in states with large heavy-machinery markets. Post-merger, three auction sites closed. The dependence of the locations affects the offline auction frequency. Texas has ten auction events every year, but there are only four large auction events each year in Maryland. Although offline auctions are less frequent than online auctions, RBA still accounts for a much larger market share than IP (approximately 4:1). One reason is that many buyers prefer the local inspection opportunities provided by the offline platform.

RBA lists the trucks it will sell in the next two months on its websites. Sellers who choose offline auctions need to transfer the trucks to the auction sites. Since sellers need to pay a high penalty fee if they withdraw the trucks in a short window, I assume that sellers conduct single-homing only. This assumption is consistent with the observation in the data. On the auction days, different auction rings sell various items simultaneously. Buyers can bid in any auction online or in-person with registration. Trucks are sold via English Auctions without reserve prices.

Figure 2: Definition of Regions



2.1.3 IronPlanet

IP is a leading pure online used truck auction platform. There is no location restriction on the online platform. Regardless of their location, all buyers have the same information regarding the trucks sold on IP and can place their bids once allowed online. On the website, information regarding the trucks sold in the next two weeks is available. IP holds auctions every Thursday. A very low starting bid is given by the platform in each auction. Buyers can choose to place a proxy bid before the auction day. On the auction day, several auctions are held almost simultaneously. Since a buyer cannot withdraw her bids in an auction, it is difficult for her to manipulate several auctions if she only has single-unit demand. The auctions proceed very quickly; thus, if a buyer loses in one auction, she loses the opportunity to participate in another auction in which she is interested.

Both RBA and IP sell heavy machinery in addition to trucks. The aggregate market share of these two platforms in the used heavy truck market is no greater than 60% since some other auction platforms exist in the market. [4]

According to the bidding data and local investigation, buyers also search for and purchase trucks in adjacent states. Therefore, in my analysis, I define "markets" at the region-month level. Figure 2 shows the four regions defined in this paper. In each market, the analysis includes all RBA auctions during that month in the region, and all IP auctions are treated as if they occur simultaneously.

[4]This information was obtained by consulting with experts in this industry.

2.2 Merger

The acquisition was announced in August 2016 and finalized in May 2017. After a second request for additional information under the HSR Act, the case received unconditional antitrust clearance from the DOJ.[5] Some policies related to both price and information changed after the merger.

First, RBA increased the commission rate of its physical auctions to make it more similar to IP. RBA and IP charge buyers different rates for different transaction prices: the rate for a lower-priced truck is proportionately higher than the rate for a higher-priced truck. Table 1 shows the commission rates of both platforms before and after the merger. The commission rate for trucks with final prices $\$5,000$ to $\$33,500$ increased from 2.5% to 3.85%. All other factors are similar. The second change that I focus on is RBA's integration

Table 1: Commission Pre- and Post-Merger

IP		RBA			
2016 & 2018		2016		2018	
Price	**Commission**	**Price**	**Commission**	**Price**	**Commission**
<10	10%	<2.5	10%	< 5	10%
10-33.5	min{3.85%, $1,000}	2.5-33.5	min{2.5%, $950}	5-33.5	min{3.85%, $500}
>33.5	$1,290	>33.5	$1,290	>33.5	$1,290

Notes: unit of the price is $1,000.

of the platform media, websites, and support teams to allow users to easily search for and request information regarding trucks on both platforms. First, RBA and IP release news and emails to provide information regarding these two platforms.[6] Second, both platforms built new websites with a cross-listing mechanism. Both RBA and IP changed their Websites. Before the merger, buyers could only find the trucks sold on the platform they entered; after the merger, buyers can easily find some information regarding the trucks sold on the other platform regardless of which website they enter (Figure A2). Finally, the platforms share the same customer service. After the merger, the customer service team of either platform can help buyers obtain information regarding the trucks sold on both platforms.

These cross-platform mechanisms enable buyers to easily find information regarding

[5] https://www.rbauction.com/media/news-releases/archives/2017/0170518-rba-ip-secure-antitrust-cleara //www.reuters.com/article/idCNASC09NTD

[6] The following is an example of news released by RBA after an offline auction in TX: *"...," said Alan McVicker, Regional Sales Manager, Ritchie Bros. "Bidders were very active, competing on a great selection of equipment consigned from more than 650 owners. For those buyers unable to get what they needed in Houston, we have an online Iron Planet auction today (Thursday, April 18) with close to 1,000 items available."* https://www.rbauction.com/news-releases/20190418-ritchie-bros-sells-us47-million-of-equipment-in-houston-tx-this-week

the trucks on both platforms, potentially decreasing the search costs in the market.

2.3 Data

The primary data set contains transaction data collected from IP's and RBA's websites. From both platforms, I obtain all transactions of used trucks from 02/01/2016 to 09/30/2016 (the pre-merger period) and from 02/01/2018 to 09/30/2018 (the post-merger period). The transaction data includes the transacted prices, truck characteristics (VIN, age, mileage, make and model), and listing characteristics (platform, transaction price, location, date, and commission fees paid to the platforms). I do not have data of other small truck auction sites. The following additional information of IP after the merger is considered: bids in auctions, each bidder's location (states), and bidding time. To obtain more information regarding the truck models, I match the trucks to the Truck Blue Book to obtain information regarding each model's suggested retail price (MSRP). I assume that the trucks in the transaction data represent an approximation of trucks available in the market. Although the data only shows the set of trucks that went transactions, as RBA uses no reserve-price auctions and IP lowers the starting prices in online auctions when there are no bidders, this assumption should be close to satisfied.

Table 2 summarizes the characteristics and transaction price of the trucks sold on both platforms before and after the merger. As shown in the table, the trucks' transaction volumes were similar before and after the merger. However, the quality distributions of the trucks sold on these two platforms changed: the trucks sold on IP are significantly older and have a significantly higher average mileage post-merger. I further discuss this analysis in the descriptive findings. Since many different observed characteristics can be used to measure trucks' quality, it will be hard to do a structural estimation to include all of them directly. Therefore, I use an additional data set to figure out a one-dimensional quality index.

The data set I use includes the registration data of trucks in Texas.[7] This data set includes transactions of used trucks in TX through all channels (retailers, wholesalers, large fleets, and auctions) from 01/01/2016 to 08/31/2018. As mentioned above, less friction exists in other channels than the auction channel, so other channels' transaction prices are more closely related to the trucks' quality. Also, the transaction does not contain RBA and IP only. Therefore, I regress the trucks' transaction price in this data set on the observed characteristics listed in Table 2 and construct the one-dimensional quality measurement. Table 3 shows the hedonic regression used to construct the quality index.

Finally, by combining the registration data with the licensing under the International

[7] Source: DMV of Texas.

Table 2: Characteristics and Prices of the Trucks Sold on IP and RBA

	2016			**2018**		
Measurements	IP	RBA	Combined	IP	RBA	Combined
Total Number	1,423	6,932	8,355	1,690	6,838	8,528
Freightliner	226	567	793	178	1,384	1,562
International	323	2,422	2,745	660	1,884	2,544
Kenworth	125	1,049	1,174	176	806	982
Mack	301	1,058	1,359	184	721	905
Others	67	323	390	216	249	465
Peterbilt	227	1,027	1,254	86	986	1,072
Volvo	154	486	640	190	808	998
Avg. Price	14,024	17,898	17,169	7,492	17,866	15,040
Avg. Age	9.70	9.27	9.35	11.85	9.12	9.66
Avg. Log(Mileage)	12.69	12.66	12.67	13.03	12.94	12.96
Avg. MSRP	72,945	75,618	75,159	71,543	79,870	78,148

Notes: 1. unit of price and MSRP is $; 2. unit of Mileage is mile.

Table 3: Hedonic Regression Used to Construct the One-Dimensional Quality Index

VARIABLES	logprice
log(mile)	-0.0438***
	(0.00351)
log(mrsp)	0.228***
	(0.0225)
Constant	3.710***
	(0.122)
Diesel Dummy	-0.0709***
	(0.0130)
Make Dummies	Y
Age Dummies	Y
Observations	46,545
R-squared	0.526

Notes: standard errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Registration Plan in Texas,[8] I can identify the trucks purchased by different types of buyers. Using the VIN as the trucks' unique identity, I can match this data set to the auction transaction data. Since Texas has the largest number of buyers according to the online bidding information, this sample is suitable for analyzing two types of buyers' behavior.

2.4 Descriptive Findings

Here, I summarize the notable findings in the data. I first illustrate some cross-sectional facts in this market and then discuss the changes pre- and post-merger.

2.4.1 Cross-sectional Variation

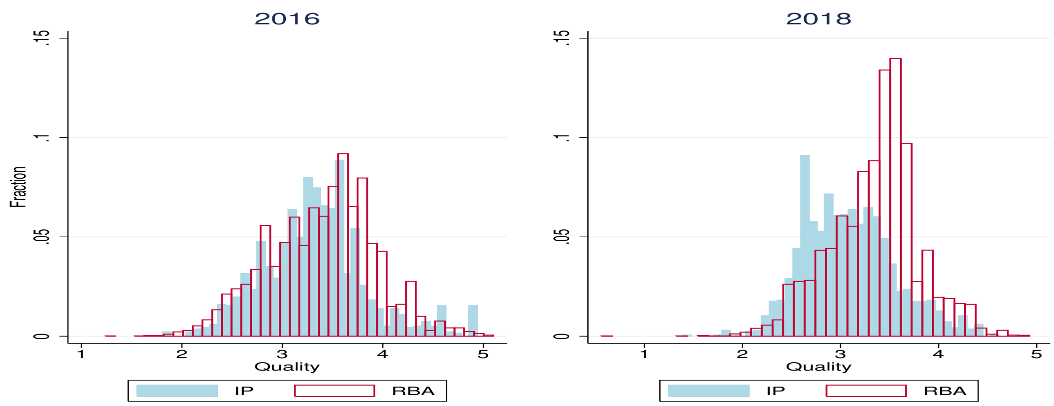
Cross-platform Facts There is a decrease in the quality of trucks sold in auctions. According to Texas's data, however, the decline in quality is also true for the trucks sold in other channels (Table A1). Therefore, I assume that the change in general quality is irrelevant to the merger, and I control it in the counterfactuals.

Comparing the quality distributions of the trucks sold on IP and RBA in 2016 and 2018 (Figure 3), I find that the average quality of the trucks sold offline is higher than that of the trucks sold online. Consistent with Table 2, this difference is much more significant after the merger: high-quality trucks are much more likely to be sold on RBA, and low-quality trucks are much more likely to be sold on IP post-merger. The reason for this change is uncertain and may be related to the sellers' platform entry choices or the platforms' reposition policy. I investigate the welfare effect and policy implication of this change in the counterfactual part.

Figure A3 presents the price distribution (the mean and variance) of trucks belonging to different quality bins. Here, each quality bin is constructed based on the one-dimensional quality measurement and rounded to the nearest integer. First, as shown in the standard deviation figure, considerable heterogeneity exists in trucks' prices with the same quality on the same platform. The price variance increases in quality, indicating that the transaction prices are not linear in the observed quality levels of the trucks. Additionally, the average transaction price of the trucks on RBA is higher than that on IP at all quality bins. One interpretation of this price difference is related to RBA's local inspection opportunity. Although IP posts the inspection reports of the trucks sold online, buyers may doubt the accuracy of the information about the trucks listed online. Therefore, buyers may discount the observed quality of the trucks sold online.

[8] Source: DMV of Texas.

Figure 3: Quality Distribution Across Platforms



Notes: quality is round to the nearest integers.

Cross-buyer Facts Using Texas data, I compare the trucks purchased by interstate trucking companies and local trucking companies. As shown in Figure A4, interstate firms tend to purchase higher quality trucks. Meanwhile, these firms also pay higher prices for these trucks conditional on buying them. This finding indicates that interstate companies may prefer to purchase high-quality trucks more than local companies.

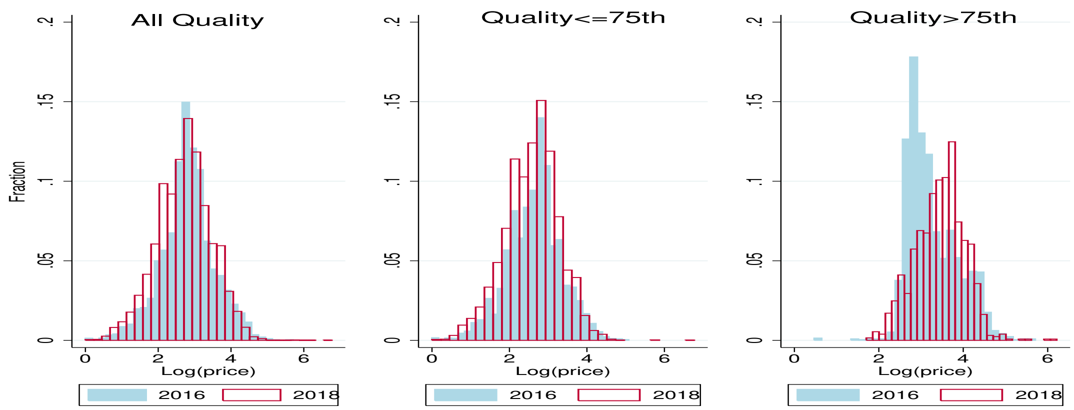
Cross-market Facts According to the definition of the markets, I calculate the number and average quality of the trucks subject to transactions in each market (Figure A5). The transaction volume is much larger on RBA and more fluctuated across markets than the one on IP. The average quality of trucks varies across markets.

2.4.2 Cross-year Variation

Next, I show some interesting changes in market outcomes following the merger.

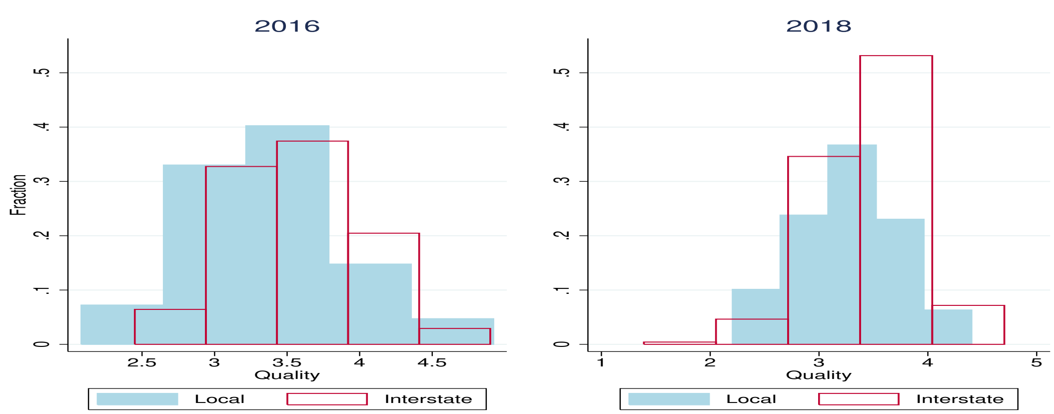
Transaction Price and Quality of Trucks The first important finding is a change in the relationship between the transaction price and the trucks' quality. I divide the trucks into different quality groups according to their percentiles. Figure 4 shows the histograms of the log(price). The higher quality trucks' prices tend to increase after the merger, although the distribution of the prices of the lower quality trucks remains approximately unchanged. The difference in the quality of the trucks purchased by different types of buyers is more significant post-merger: compared with local trucking companies, interstate trucking companies are more likely to purchase the high-quality trucks post-merger (Figure 5).

Figure 4: Price Distributions of Trucks in Different Quality Groups



Notes: unit of price is $1,000.

Figure 5: Quality Distributions of Trucks Purchased by Different Types of Buyers



Transaction Price and Trucks Available on Each Platform The final remarkable change is related to the relationship between the transaction price and trucks available on each platform in the market. To analyze the change in this relationship, I use the number of trucks on each platform and the average quality of these trucks as two main measurements representing the available trucks. Since the quality and number of trucks fluctuated more on RBA, I regress an online truck's price on its quality and these measurements. I conduct this regression pre-merger and post-merger separately (Table 4). One robust finding is that a truck's price on IP is more sensitive to the average quality of the trucks on RBA. When the average quality of the trucks sold on RBA is high, trucks' transaction price on IP tends to be low post-merger if everything else remains the same.

Table 4: Sensitivity of Price on IP to the Trucks Available on Each Platform

	2016	2016	2018	2018
VARIABLES	log(price)	log(price)	log(price)	log(price)
$quality$	1.086***	1.164***	0.790***	-2.689***
	(0.0390)	(0.298)	(0.0373)	(0.349)
$quality^2$		-0.0115		0.547***
		(0.0434)		(0.0545)
$\overline{quality_{-j}^{IP}}$	0.430***	0.433***	0.285*	0.0855
	(0.119)	(0.119)	(0.162)	(0.158)
$\overline{quality^{RBA}}$	0.0400	0.0359	-0.657***	-0.450**
	(0.105)	(0.106)	(0.221)	(0.215)
N^{IP}	-0.001*	-0.001*	-0.001**	-0.002***
	(0.001)	(0.001)	(0.001)	(0.001)
N^{RBA}	0.000	0.000	-0.000**	-0.000*
	(0.000)	(0.000)	(0.000)	(0.000)
Constant	-2.284***	-2.409***	1.325*	6.661***
	(0.619)	(0.779)	(0.802)	(0.940)
Observations	1,354	1,354	1,470	1,470
R-squared	0.456	0.456	0.258	0.305

Notes: standard errors in parentheses $***p < 0.01, **p < 0.05, *p < 0.1$.

Summary In summary, we can observe that after the merger: (1) compared with the low-quality trucks, the probability of selling high-quality trucks at high prices increases after the merger; (2) compared with local trucking companies, interstate trucking companies are more likely to purchase high-quality trucks; (3) the price distribution on IP is more sensitive to the quality of trucks available on RBA in the same market.

I show that the change in search costs can potentially explain these three findings.

3 Model

This section presents a model of the platform markets that endogenizes buyers' search, auction entry, and auction bidding. I assume that trucks with different quality levels are sold in single-unit auctions on two platforms. My model treats the supply-side as exogenous while developing an equilibrium model of buyers' behavior. Given their private draws of search costs, buyers simultaneously choose whether to search both platforms and how many auctions to search. Searching allows buyers to discover the characteristics and private values of individual trucks. Then, buyers simultaneously decide which of the searched auctions to enter. Buyers have a unit demand and can enter exactly one auction. The model is static because I do not allow buyers to consider the possibility of entering subsequent auctions if they fail to purchase a truck in the auction market.

3.1 Sellers

The realized set of trucks available on each platform is drawn from the observed sets of trucks in the data across regions and time periods. The information regarding the trucks available on each platform includes the realized quality levels (q), namely, the one-dimensional quality index, of the trucks on each platform and the number of trucks at each quality level on each platform.

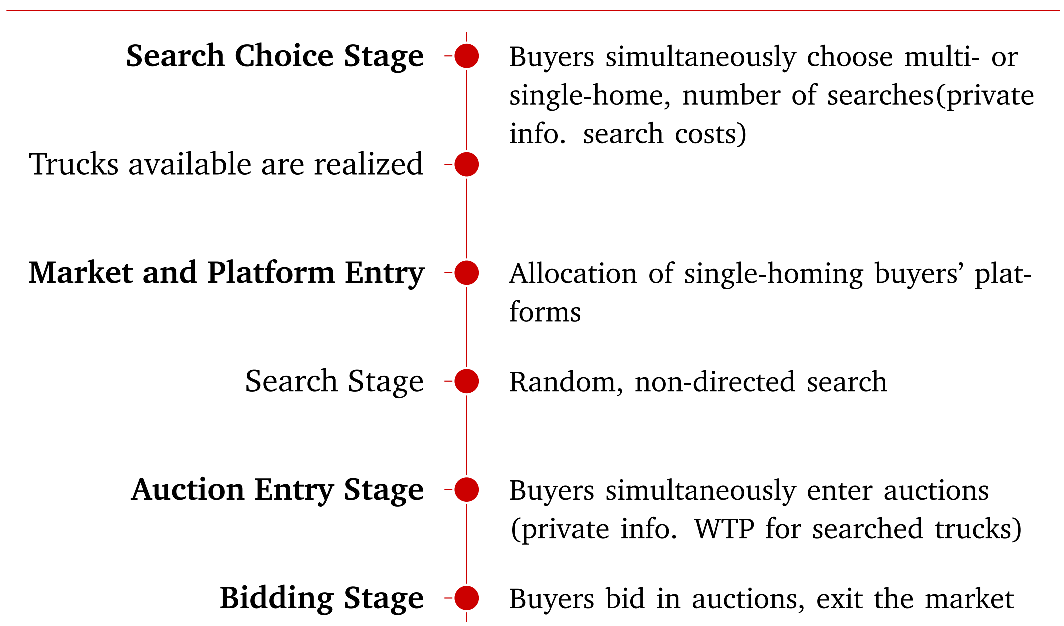
3.2 Buyers

All buyers are ex-ante symmetric but distinguished by their i.i.d draws of fixed search cost ($fc \sim H^{fc}(\cdot)$), marginal search cost ($mc \sim H^{mc}(\cdot)$), and private value of each truck (v). A buyer's WTP of a truck depends on the quality of the truck and the her private value for that truck. I make the following assumption regarding the buyers' WTP.

Assumption 1. ***Distribution of WTP*** *A buyer's WTP for a truck follows a log-normal distribution as follows:* $V = exp(\theta q + v), v \sim N(\mu, \sigma)$.

Assumption 1 places the restriction on the WTP that q and v are not additively separable. The multiplicative structure $\frac{\partial V^2(q,v)}{\partial q \partial v} > 0$ indicates that the values are always positive and consistent with the fact that the variance of the realized prices increases with quality. A log-normal distribution is also a type of distribution commonly used in the auction literature (e.g., Laffont et al. [1995]). The specific form that I use also allows for a WTP discount ($\alpha < 0$) for online trucks, specifically, the WTP of a buyer with private value v for a truck with quality q online is $V = exp(\theta(q + \alpha) + v)$.

Figure 6: Timeline of the Game



In addition to this baseline model, I also consider a model with two types of buyers who can have different quality preferences, where the draws are i.i.d. within types, and the mix of types fit the interstate/local data from TX. I allow different types of buyers to have different coefficients of θ^H and θ^L for quality.

3.3 Timing

Figure 6 shows the timeline of the game.

- **Search Choice Stage** During this stage, buyers draw private search costs independently from the cost distributions. Based on the private search costs and common knowledge (distribution search costs, distribution of WTP, and distribution of trucks available on each platform), buyers simultaneously determine their search choices. A search choice includes the following two parts:
  - Search frequency ($m \in \{1, ..., M\}$): number of trucks to search under either homing choice.
  - Homing choice ($\text{home} \in \{\text{multi}, \text{single}\}$):
    * Single-homing: a buyer searches trucks randomly on one platform;

  * Multihoming: a buyer searches trucks randomly on both platforms.

  To reduce the computation burden, I assume when buyers make their search choices, they have no information regarding the realized available trucks in the market and only know the distribution of a possible set of trucks available on each platform.

- **Market and Platform Entry** Buyers enter the market based on the realized number of trucks in the market, and single-homing buyers enter a platform. I assume this process is exogenously determined. Specifically, I make the following assumption:

Assumption 2. ***Market and Platform Entry*** *When the realized numbers of trucks sold on Platform A and Platform B in a market are N^A and N^B,*

- *Market Entry: $\gamma \times (N^A + N^B)$ buyers enter the market, where γ is a scalar parameter and exogenously determined.*

- *Platform Entry: the probability of a single-homing buyer entering one platform is given according to a random entry rule which depends on the number of goods on each platform in that market $Prob(A) = \frac{N^A}{N^A+N^B}, Prob(B) = \frac{N^B}{N^A+N^B}$.*

When doing estimation, γ is calculated from bidding data. Under the random entry rule, all trucks on both platforms have the same probability to be chosen. The only difference between single-homing buyers and multihoming buyers is the composition of the searched trucks they can choose when making their auction entry choices. In reality, an implication of this assumption is that single-homing buyers' platform choice is closely related to the scarcity of offline auctions in that market. In a market, there are many offline auctions, buyers tend to single-homing offline; otherwise, they are more likely to single-homing online. Additionally, I consider alternative rules where buyers can target a specific platform when they conduct single-homing in the estimation part.

- **Auction Entry Stage** After randomly searching in the market, buyers simultaneously make their auction entry choice (e). They determine which of the searched auctions to enter according to the information regarding the searched trucks.

- **Auction Bidding Stage** After entering auctions, buyers submit their bids (b) in the auctions. The trucks are sold via English auctions. They leave the market regardless of whether they win.

When describing the equilibrium, I will use superscripts $\{A, B\}$ to denote different platforms, subscripts $i \in \{1, ..., N_{buyer}\}$ to represent a buyer and $j \in \{1, ..., N\}$ to represent a truck.

3.4 Equilibrium

The equilibrium of this game is defined as follows.

Definition 1. ***(A Symmetric Bayesian Nash Equilibrium for Buyers)***

A symmetric Bayesian Nash equilibrium in the market for buyers with common knowledge is a set of search strategies $\{m^*(\cdot), home^*(\cdot)\}$, auction entry strategies $e^*(\cdot)$, and bidding strategies $b^*(\cdot)$ such that any buyer

- *bids optimally*
- *enters a searched auction according to an optimal rule*
- *decides how to search based on an optimal rule*

given the equilibrium strategies of the other buyers in each stage.

The game can be solved by backward induction. I describe the equilibrium starting from the bidding stage.

3.5 Auction Bidding and Entry Stage

In the bidding stage, a buyer's private information is her WTP for the truck sold in the auction she enters: $V(q,v)$. Given this private information, she makes her bidding decision. Since the auction is an IPV English auction, truthfully bidding is the dominant strategy for all buyers, we have $b^*(V(q,v)) = V(q,v)$. [9]

In the auction entry stage, after searching, buyers have private information regarding the searched trucks. I denote the private information of buyer i who searched m trucks under homing choice home as $(\mathbf{q}_i^{m,\text{home}}, \mathbf{v}_i^{m,\text{home}})$, where $\mathbf{q}_i^{m,\text{home}}$ and $\mathbf{v}_i^{m,\text{home}}$ are $m \times 1$ vectors, $\mathbf{q}_i^{m,\text{home}}$ includes the quality information regarding these m trucks and $\mathbf{v}_i^{m,\text{home}}$ includes the private values associated with these trucks. Given the private information, buyers make their entry choice. Buyer i's entry strategy is a $m\times 1$ vector $e_i(\mathbf{q}_i^{m,\text{home}}, \mathbf{v}_i^{m,\text{home}})$, where all the elements are zeros but the chosen one.

[9] When platforms charge a commission from buyers, buyers' bids equal their WTP discount by the commission rate in the English auction. This can completely transfer the burden of the commission from the buyers to sellers if there is no reserve price, we do not consider sellers' platform entry choices, and all buyers have single-unit demand.

The expected payoffs from entering an auction depend on the expected competition in that auction. In the view of other buyers, $Pr_i^e(q_j, v_{ij})$ is the probability that buyer i will enter auction j with a private value no less than v_{ij}. Similarly, in the view of buyer i, $Pr_l^e(q_j, v_{lj})$, $\forall l \neq i$ is the probability that buyer l will enter auction j with a private value no less than v_{lj}. Then, buyer i's expected payoffs from entering an auction with quality q_j and private value v_{ij} is as follows:

$$U_i(q_j, v_{ij}) = \begin{cases} \int_{\underline{v}}^{v_{ij}} [V^A(q_j, v_{ij}) - V^A(q_j, \tilde{v})] d\Pi_{l\neq i}[1 - Pr_l^e(q_j, \tilde{v})] + \ldots \\ \qquad V^A(q_j, v_{ij})\Pi_{l\neq i}[1 - Pr_l^e(q_j, \underline{v})] & \text{if } j \text{ is on } A \\ \int_{\underline{v}}^{v_{ij}} [V^B(q_j, v_{ij}) - V^B(q_j, \tilde{v})] d\Pi_{l\neq i}[1 - Pr_l^e(q_j, \tilde{v})] + \ldots \\ \qquad V^B(q_j, v_{ij})\Pi_{l\neq i}[1 - Pr_l^e(q_j, \underline{v})] & \text{if } j \text{ is on } B \end{cases} \tag{1}$$

In equation (1), $\Pi_{l\neq i}[1 - Pr_l^e(q_j, \tilde{v})]$ is the probability that no buyers but i enters the auction with quality q_j and random value no less than $\tilde{v}$.

According to the definition of BNE, an equilibrium entry strategy should maximize buyer i's expected payoffs. A buyer will enter the auction with the highest expected payoff in the set of auctions she has searched. So in equilibrium, the buyer $i's$ entry probability defined above equals

$$\begin{aligned} Pr_i^{e*}(q_j, v_{ij}) = \sum_{m,\text{home}} \sum_{\mathbf{q}_i^{m,\text{home}}} [\int_{\underline{v}}^{\overline{v}} \ldots \int_{\underline{v}}^{\overline{v}} \int_{v_{ij}}^{\overline{v}} \mathbf{I}\{q_j \in \mathbf{q}_i^{m,\text{home}}\} \times \ldots \\ \mathbf{I}\{U(q_j, v) = \max\{U(q_{j'}, v_{ij'})\}_{(q_{j'}, v_{ij'}) \in (\mathbf{q}_i^{m,\text{home}}, \mathbf{v}_i^{m,\text{home}})}\} \ldots \\ dF(\mathbf{v}_i^{m,\text{home}}) Prob(\mathbf{q}_i^{m,\text{home}}) Prob(m_i = m, \text{home}_i = \text{home}) \end{aligned} \tag{2}$$

where $\mathbf{I}\{\cdot\}$ are two indicator functions represent the event that truck j is searched and the auction with (q_j, v) has the highest expected payoffs in the set of trucks searched by buyer i.

As equation (2) shows, the probability is determined by the distribution of buyer i's search choice $\{Prob(m_i = m, \text{home}_i = \text{home})\}$, probability of searching different sets of information including truck j conditional on a search choice and the probability to choose auction j with the searched information.

We can transfer the BNE into probability space.[10] Formally, according to (1) (2), the

[10] There are many other papers, Seim [2006], Aguirregabiria and Mira [2007] , etc, treat BNE as being in probability space. Note that here the probabilities come from the different sets of information buyers can get from the random search process, not logit errors.

symmetry of buyers and the difference between platforms, the problem can be written as

$$\begin{pmatrix} Pr^{e^*}(q,v,A) = \Lambda^{e,A}(Pr^{e^*}(q,v)) \\ Pr^{e^*}(q,v,B) = \Lambda^{e,B}(Pr^{e^*}(q,v)) \end{pmatrix}$$

where $\Lambda^{e,A}$ and $\Lambda^{e,B}$ are the best response probability functions and

$$Pr^{e^*}(q,v) = \begin{pmatrix} Pr^{e^*}(q,v,A) \\ Pr^{e^*}(q,v,B) \end{pmatrix}$$

Since the best response probability functions are well defined and continuous in the compact convex set of players' probabilities, according to Brouwer fixed-point theorem, at least one equilibrium exists. [11]

Given the equilibrium probabilities, I can obtain a set of equilibrium expected payoffs $U^*(q,v)$. A buyer's expected payoffs from a set of auctions are the payoffs from the auction with the highest $U^*(q,v)$ in the set. Based on Assumption 2, I can calculate the expected payoffs from different search choices given the realized trucks available in the market.

3.6 Search Choice Stage

In the first stage, buyers' private information is their search costs. They decide their homing choices and search frequencies according to their private information.

Since buyers make the choices before they discover the set of trucks available on each platform, the expected payoffs should be average across all possible realizations of available trucks on each platform. I denote buyer i's expected payoffs from a search choice W_i. According to equation (2), the expected payoffs depend on the distribution of other buyers' search choice. This distribution is the conditional choice probability (Aguirregabiria and Mira [2007]) associated with a search strategy of a buyer given the distributions of search costs. Define $Pr_i^{m,\text{home}} = Prob(m_i = m, \text{home}_i = \text{home}), \forall i, Pr_{-i}^{m,\text{home}} = \{Prob(m_l = m, \text{home}_l = \text{home}), \forall l \neq i\}$. In equilibrium, buyer i choose m_i and home_i that can maximize

[11] It is easy to show that the expected payoff functions U is continuous and monotonically increasing in v. In other words, $\forall q$, my expected payoffs to the auction with q will be continuous and increasing in v. Under the optimal rule, buyers choose to entering the auction with the highest expected payoffs. According to equation (1)(2), as the probability of other people (using their optimal rule) entering auctions increases, my best response will fall continuously.

her net expected payoffs given $Pr_{-i}^{m^*,\text{home}^*}$

$$\max_{m_i,\text{home}_i} [W_i(m_i, \text{home}_i, Pr_{-i}^{m^*,\text{home}^*}) - mc_i \times m_i - \mathbf{I}\{\text{home}_i = \text{multi}\} \times fc_i]$$

where $\mathbf{I}\{\text{home}_i = \text{multi}\}$ is the indicate function that buyer i choose multihoming.

So there are two equilibrium conditions that (m^*, home^*) and Pr^{m^*,home^*} should satisfy. The first condition ensures that no one wants to deviate to a different number of searches given their private marginal search costs and the homing choices. Since the expected marginal gain from an additional search decreases with the number of searches,[12] we can find the equilibrium cutoffs at which buyers feel indifferent towards searching different numbers of trucks under the same homing strategy.

$$\begin{cases} W_i(m^*+1, \text{home}^*, Pr_{-i}^{m^*,\text{home}^*}) - W_i(m^*, \text{home}^*, Pr_{-i}^{m^*,\text{home}^*}) = \underline{mc}(m^*, \text{home}^*) \\ W_i(m^*, \text{home}^*, Pr_{-i}^{m^*,\text{home}^*}) - W_i(m^*-1, \text{home}^*, Pr_{-i}^{m^*,\text{home}^*}) = \overline{mc}(m^*, \text{home}^*) \end{cases} \tag{3}$$

Second, to ensure that no buyer has an incentive to deviate her homing choice with her search costs, I need to compare the expected payoffs from the proposed equilibrium strategy with the optimal search strategy under the other homing strategy. Therefore, the second set of equilibrium conditions is as follows:

$$\begin{cases} W_i(m^*, \text{single}, Pr_{-i}^{m^*,\text{home}^*}) - mc_i \times m^* \geq ... \\ \max\{W_i(m, \text{multi}, Pr_{-i}^{m^*,\text{home}^*}) - mc_i \times m_i\} - fc_i, \\ \max\{W(m, \text{single}, Pr_{-i}^{m^*,\text{home}^*}) - mc_i \times m_i\} \leq ... \\ W_i(m^*, \text{multi}, Pr_{-i}^{m^*,\text{home}^*}) - mc_i \times m^* - fc_i. \end{cases} \tag{4}$$

The first inequality is for the case that $\text{home}^* = \text{single}$ and the second inequality is for the case that $\text{home}^* = \text{multi}$. (4) indicates that given a marginal cost, a buyer will choose multihoming only if her fixed cost is lower than a threshold.

Based on (3) and (4), the conditional choice probabilities can be calculated given the distributions of the marginal search cost and fixed search cost. For example, the probability

[12]Since the expected payoff function is the expectation of the largest order statistics, it is concave in the number of searches (David [1997]).

of (m, multi) is as follows:

$$Pr_i^{m^*,\text{home}^*}(m,\text{multi}) = \int_{\underline{mc}(m,\text{multi})}^{\overline{mc}(m,\text{multi})} \int_{\underline{fc}}^{fc(mc_i)} h^{mc}(mc_i) h^{fc}(fc_i) dfc_i dmc_i \tag{5}$$

where $fc(mc_i) = W_i(m^*, \text{multi}, Pr_{-i}^{m^*,\text{home}^*}) - ...$

$mc_i \times m^* - \max\{W_i(m, \text{single}, Pr_{-i}^{m^*,\text{home}^*}) - mc_i \times m_i\}$

and $\underline{fc}$ is the lower bound of fixed cost.

Therefore, in the symmetric BNE, we have

$$Pr^{m^*,\text{home}^*} = \Lambda^m(Pr^{m^*,\text{home}^*}),$$

where Λ^m is the best response probability function. According to (3), (4) and (5), Λ^m is well defined and continuous in the compact convex set of the buyers' choice probabilities. Based on the Brouwer fixed-point theorem, at least one equilibrium exists.

Given the equilibrium of the game, next, I will discuss the economics of search choices and show how the change in search costs can affect the market outcome.

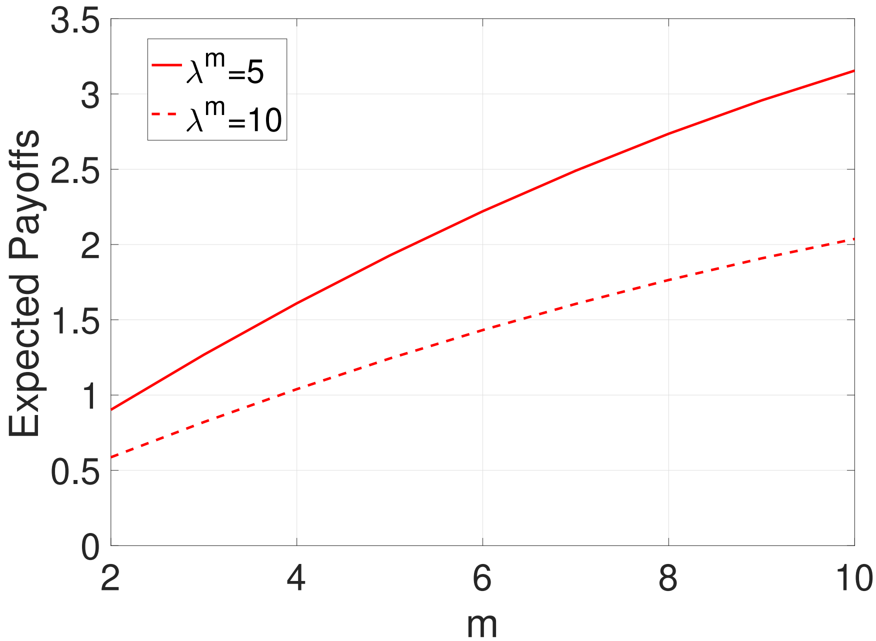
3.7 Economics of Search

3.7.1 Search Frequency

Buyers are more likely to find trucks with higher expected payoffs when they search for more trucks. Therefore, a buyer's expected payoffs increase in the numbers of searches. The marginal cost of searching one more truck is the effort required to investigate the quality of the truck and determine the private value of the truck, such as online search and consulting with sales representatives, etc. A buyer decides the number of trucks to search for by trading off between the gain and cost of the marginal search.

When a buyer has lower marginal search cost, she has an incentive to search for more trucks. However, other buyers will also have this motivation when they draw lower marginal search costs. Searching is strategic substitution among buyers because an increase of other buyers' search frequency results in more competition in auctions with high expected payoffs and reduces the gain from more searches. Figure 7 shows one example of expected payoff functions from different searches $W(m, \text{home}^*)$ under the same homing choice. The average number of searches chosen by other buyers (λ^m) increases from five to ten, resulting in a flatter expected payoff function. This indirect effect can partly discourage buyers from searching for more goods. However, in the new equilibrium with

Figure 7: Net Expected Payoffs $W(m, \text{home}^*)$ When $\lambda^m = 5$ and $\lambda^m = 10$



Notes: unit of expected payoffs is $\$1,000$.

average lower marginal search costs, the average number of searches among buyers is still higher than the one in the old equilibrium. With more searches in the new equilibrium, the distribution of transaction price will change. Here, I give an example about how the price will change under a simple structure of available trucks in the market.

Proposition 1. *(**Change in Search Frequency**) If (1) there is one platform; (2) there are two types of trucks differentiated by their observed quality levels q^H and q^L, where $q^H > q^L$; (3) buyers in the market choose to search one or two trucks and the equilibrium probability of buyers to search two trucks under different distributions of search costs are Pr^{m^*} and $Pr^{m^{**}}$, where $Pr^{m^*} < Pr^{m^{**}}$, then the difference between the upper tail of the price distribution of high-quality trucks and that of low-quality trucks increases when buyers tend to search two trucks. Formally, using p to denote final prices, we have*

$$\begin{aligned}
&\exists p^*, \forall \tilde{p} \in [p^*, \overline{p}] \\
&Prob(p > \tilde{p} | q^H, Pr^{m**}) - Prob(p > \tilde{p} | q^L, Pr^{m**}) \geq ... \\
&Prob(p > \tilde{p} | q^H, Pr^{m*}) - Prob(p > \tilde{p} | q^L, Pr^{m*})
\end{aligned} \tag{6}$$

Proof. See Appendix B.1.1. □

In addition to the formal proof in the appendix, here, I briefly present the intuition about this proposition. First, given Assumption 1, I can prove that there is always a threshold of private value above which high-quality trucks are more attractive than low-quality trucks. Without changing the belief about other buyers, when buyers search for two trucks, the auctions with high-quality trucks are more likely to be chosen by buyers with private value above the threshold in the original equilibrium. Then, when all buyers are more likely to search for two trucks, the competition in those high-quality auctions is fiercer. Expecting this, some buyers with moderate private values associated with the high-quality trucks may switch to auctions with low-quality trucks. Namely, the threshold in the new equilibrium will be higher. However, buyers, drawing private values above the new threshold, are more likely to choose auctions with high-quality trucks. Finally, since the transaction price is the second-highest WTP in that auction, relative to low-quality trucks, high-quality trucks are more likely to be transacted with higher prices when buyers search more intensively.

For markets with more complicated structures of available trucks, the change in buyers' auction entry behavior follows a similar pattern when they tend to search for more trucks. In Appendix B.2, I use simulations to illustrate this. Additionally, I give a discussion about a model with two types of buyers and show that buyers with high quality preference are more likely to purchase high-quality trucks than low-type buyers when the marginal search costs are lower.

The analysis above shows that the cross-year change (1)(2) observed in the data can be explained by higher search frequency. This mechanism is also useful to justify identification, which I will discuss later.

3.7.2 Homing Choices

When buyers engage in multihoming, they can access a set of trucks from two platforms and choose the platform having auctions with the highest expected payoffs in their choice set, which can smooth the variation in the number and quality across the platforms, and may increase buyers' expected payoffs. The fixed costs of multihoming include learning the two systems, registering two accounts to monitor trucks, etc. Buyers make their homing choices by trading-off between the gain from multihoming and these costs. When the fixed costs decrease, more buyers switch to multihoming.

The increased share of multihoming buyers can change the market outcome. Similar to search frequency, I also show the pattern in a simple setting.

Proposition 2. *(**Change in Homing Choices**) If (1) there are two platforms and all the trucks on the same platform have the same quality level; (2) there are two observed quality levels q^H and q^L, where $q^H > q^L$; (3) buyers in the market choose to search one or two trucks and the share of single-homing buyers under different fixed search costs are ω^* and ω^{**}, where $\omega^* > \omega^{**}$, then the difference between the upper tail of the price distribution of a truck on platform A when the average quality of the trucks on platform B is low and that when the average quality of the trucks on platform B is high increases if there are more buyers conduct multihoming. Formally,*

$$\begin{aligned}
&\exists p^*, \forall \tilde{p} \in [p^*, \overline{p}] \\
&Prob(p^A > \tilde{p} | \overline{q}^B = q^L, \omega^{**}) - Prob(p^A > \tilde{p} | \overline{q}^B = q^H, \omega^{**}) \geq \ldots \\
&Prob(p^A > \tilde{p} | \overline{q}^B = q^L, \omega^{*}) - Prob(p^A > \tilde{p} | \overline{q}^B = q^H, \omega^{*})
\end{aligned}$$

Proof. See Appendix B.1.2. □

The proposition is based on a similar logic in Proposition 1. The expected payoffs of high-quality trucks are always higher than those of low-quality trucks if the private values drawn by buyers are above some threshold. Therefore, buyers with high private values are more likely to choose Platform B if the trucks on Platform B have high quality. This can explain the change in price distribution shown in Proposition 2.

This proposition shows that the cross-year change (3) observed in the data can be explained by buyers' more multihoming. It will also be called in the identification.

Finally, the change in the fixed costs may alter the search frequency, and the change in the marginal costs may alter the multihoming choices. For example, under multihoming, there are more variations in the composition of trucks in a choice set. Thus, the expected payoff function is less concave under multihoming when the number of searches is large. Namely, the expected payoffs from searching many trucks are higher under multihoming than the one under single-homing. Therefore, lower fixed search costs can encourage buyers to search for more trucks.

Based on the analysis and propositions above, the cross-year descriptive findings in the data can be explained by the reduction in search costs.

4 Identification

In this section, I explain how to identify the two critical components in the model, i.e., the distribution of buyers' WTP and the distribution of search costs. In general, the distribution of search costs is not nonparametrically identified. However, I can still identify the marginal search costs associated with the thresholds between searching different numbers of trucks and the fixed search costs associated with the thresholds between multihoming and single-homing. For simplicity, I refrain from considering post-merger changes and commission and focus on identifying the buyers' WTP and the search cost thresholds.

Definition 2. *A model is identified iff* $\forall(H^c, F^V, \hat{H}^c, \hat{F}^V)$,
$(P, B|H^c, F^V, X) = (\hat{P}, \hat{B}|\hat{H}^c, \hat{F}^V, X)$ *implies* $H^c = \hat{H}^c$ *and* $F^V = \hat{F}^V$. *where*

- *Exogenous Variables (X): set of realized available trucks on each platform and* γ*;*
- *Model Primitives* (H^c, F^V)*: the distribution of buyers' search costs and WTP;*
- *Observed Endogenous Outcomes* (P, B)*: the realized transaction price and trucks, and number of bidders in each auction.*

As shown in the model, buyers make their search strategies before entering any market. In the auction entry stage, the distribution of equilibrium search choices is a sufficient statistic for a buyer to make her optimal entry strategy. Therefore, I can separate the identification problem into the following two problems: (1) the observed distribution of the transaction prices and number of bidders can identify the distribution of WTP and distribution of buyers' equilibrium search choice ($Pr^{\mathrm{m}^*,\mathrm{home}^*}$) given the exogenous variables, and (2) the identified distribution of WTP and distributions of equilibrium search choice can identify the bounds of distributions of search costs.

Similar to the discussion about economics of search, I use the case in which all buyers search one or two trucks to show how the model can be identified. The proportion of searching for two trucks is Pr^{m^*}, and the proportion of single homing buyers is ω^* in equilibrium.

4.1 Distributions of WTP and Equilibrium Search

4.1.1 Baseline: One Platform and One Type of Buyers

I begin with markets with one platform, one type of buyers and trucks in two quality levels (q^H and q^L). Using the observed endogenous outcomes in these markets, I can prove identification.

Given the number of bidders, I can focus on the auctions with a small number of bidders. For example, from the data, I can calculate the price distribution of trucks with quality q^H conditional upon having two buyers in the auctions. This situation includes the following two cases: both buyers in an auction bid lower than p and only one buyer bids lower than p in an auction. Formally, the CDF of the transaction price for these auctions are as follows:

$$
\begin{aligned}
&F_{2,\text{price}}(p|q^H, q^L, N^H, N^L) = \ldots \\
&\underbrace{\{(1-Pr^{m^*})F^v(log(p)-\theta q^H) + Pr^{m^*}[\frac{N^H-1}{2(N-1)}(F^v(log(p)-\theta q^H))^2 + \ldots \\
&\frac{N^L}{N-1}\int_{\underline{v}}^{log(p)-\theta q^H} f^v(v)F^v(v'|U^*(q^L,v') = U^*(q^H,v))dv]\}^2}_{\text{both buyers bid lower than } p} + \ldots \\
&2\{(1-Pr^{m^*})[1-F^v(log(p)-\theta q^H)] + Pr^{m^*}[\frac{N^H-1}{2(N-1)}(1-(F^v(log(p)-\theta q^H))^2) + \ldots \\
&\frac{N^L}{N-1}\int_{log(p)-\theta q^H}^{\overline{v}} f^v(v)F^v(v'|U^*(q^L,v') = U^*(q^H,v))dv]\} \times \ldots \\
&\{(1-Pr^{m^*})F^v(log(p)-\theta q^H) + Pr^{m^*}[\frac{N^H-1}{2(N-1)}(F^v(log(p)-\theta q^H))^2 + \ldots \\
&\underbrace{\frac{N^L}{N-1}\int_{\underline{v}}^{log(p)-\theta q^H} f^v(v)F^v(v'|U^*(q^L,v') = U^*(q^H,v))dv]\}}_{\text{one buyer bids higher than } p\text{, one bids lower than } p}
\end{aligned} \tag{7}
$$

Here, $N = N^H + N^L$ and $F_{2,\text{price}}(p|q^H, q^L, N^H, N^L)$ is calculated using the data. According to the model, v' is the private value which makes buyers feel indifferent between the auction with q^H and q^L. Under Assumption 1, $F^V(\cdot|q)$ is determined by μ, σ and θ.

Proposition 3. *The price distribution function $F_{2,price}(\cdot|q^H, q^L, N^H, N^L), \forall\ q^H, q^L,\ N^H,\ N^L$ can identify the model primitives $F^V(\cdot|q)$ and Pr^{m^*}.*

Proof. See Appendix C.1. □

Here, I describe the basic idea underlying the identification. As shown in the expression of price distribution in (7), the price distribution depends on a mixture of the following three distributions: the distributions of WTP for trucks with quality q^H and q^L and the distribution of search frequency, which is simplified as the coefficient Pr^{m^*}. To separately identify these distributions, I need to use the variation in price distributions from markets with different structures of available trucks.

Assume there are two sets of model primitives can generate the same price distributions in markets where all trucks have quality q^H and markets where all trucks have quality q^L.

They cannot generate the same price distribution in markets having trucks with both q^H and q^L. As shown in the model part (Proposition 1), when buyers search for more trucks, the trucks with q^H are more likely to be purchased at a high price. If buyers search for two trucks, the difference in the price distribution in these market differs from the difference in the price distribution in the market with one quality trucks. However, the differences are the same when buyers always search for one truck.

This idea can be applied to markets with more quality levels if we can observe the price distribution in markets with various structures of available trucks.

4.1.2 Extensions

Two Platforms Assume that buyers' WTP for trucks with the same quality level differs if the goods are listed on different platforms. I denote the distributions of WTP as $F^{V,A}$ and $F^{V,B}$. Buyers also choose to conduct single-homing or multihoming, and the equilibrium probability of conducting single-homing is ω^*. To reduce the number of primitives to identify, here I make the following assumption:

Assumption 3. $Pr^{m^*,single} = Pr^{m^*,multi} = Pr^{m^*}$

According to the baseline model results, I can use the price distributions in markets only with platform A to determine the WTP on platform A and Pr^{m^*}. It is similar to markets only with platform B. An additional initial condition is needed to identify ω^*. One way to get this condition is to use the price distributions in markets with q^H on a platform and q^L on another platform. As discussed in the model part (Proposition 2), the price distribution in these markets and price distribution in markets with one platform are different when the share of multihoming buyers changes.

Two Platforms and Two Types of Buyers In this model, the share of different types of buyers is the same across different markets. In addition to the price distribution of trucks, the types of winners in the auctions are observed. Similarly, I make the following assumption to simplify the identification problem. This assumption and Assumption 3 are kept in estimation.

Assumption 4. $Pr_H^{m^*,single} = Pr_H^{m^*,multi} = Pr_H^{m^*}, Pr_L^{m^*,single} = Pr_L^{m^*,multi} = Pr_L^{m^*}$

As shown in the extended model above, using the price distributions of trucks with different quality levels, it is possible to identify $\{F^{V,A}, F^{V,B}, Pr^{m^*}, \omega^*\}$. This set of statistics can be derived from the underlying model primitives
$\{F_H^{V,A}, F_L^{V,A}, F_H^{V,B}, F_L^{V,B}, Pr_H^{m^*}, Pr_L^{m^*}, \omega_H^*, \omega_L^*\}$.

Consider the markets with one platform in each market where the quality of the trucks is the same. Since the share of different types of buyers is the same across different markets, the distribution of equilibrium search choices of both types of buyers is the same in these markets. Given a distribution of search choices $\{Pr_H^{m^*}, Pr_L^{m^*}, \omega_H^*, \omega_L^*\}$, the difference between price distribution of trucks with the same quality purchased by the same type of buyers but on different platforms can identify the difference between the same type of buyers' WTP on different platforms:$\{F_H^{V,A} - F_H^{V,B}, F_L^{V,A} - F_L^{V,B}\}$. By combing with the identified $\{F^{V,A}, F^{V,B}\}$, I can express everything as functions of buyers' search choices. Finally, as discussed in the model, using the difference in the quality distribution of the trucks purchased by different types of buyers, $\{\omega_H^*, Pr_H^{m^*}, \omega_L^*, Pr_L^{m^*}\}$ can be identified separately given $\{\omega^*, Pr^{m^*}\}$.

Figure A9 in Appendix C.2 gives a summary the measurements and assumptions used to identify different models.

4.2 Distribution of Search Costs

Given the distribution of WTP F^V and equilibrium search choice (Pr^{m^*}, ω^*), I can partially identify the distribution of the search costs according to the equilibrium conditions in the model.

Specifically, given the cutoffs constructed by (3) and (4), I can map the distribution of equilibrium search choices to the distributions of the search cost. The probability of a buyer searching for two trucks on two platforms equals the probability that the buyer's marginal search cost falls into a range and her fixed search cost is lower than a threshold.

$$(1-\omega^*)Pr^{m^*} = \int_{\underline{mc}(F^V, Pr^{m^*}, \omega^*)}^{\overline{mc}(F^V, Pr^{m^*}, \omega^*)} \int_{\underline{fc}}^{fc(mc_i, F^V, Pr^{m^*}, \omega^*)} h^{mc}(mc_i) h^{fc}(fc_i) dfc_i dmc_i$$

Similarly, I can map the probability of single-homing to a range of the marginal cost and fixed cost. Notably, there is no overlap of the fixed search cost which can support the different homing behavior performed simultaneously given the same marginal cost. For the lowest and highest assumed M, I cannot identify the upper and lower bounds; thus, I make assumptions to identify these mass points.[13]

[13] I make the following assumptions: (1) the upper bound of the marginal search cost at $M = 1$ equals the expected payoffs from searching for one truck; (2) the lower bound of the marginal search cost at $M = 10$ equals zero; and (3) the upper bound of the fixed cost of single-homing buyers equals the highest lower bound of the fixed costs of single-homing buyers.

5 Estimation

As shown above, the model can be nonparametrically identified in two steps. I still use a two-step algorithm to estimate the model. To simplify the estimation, I introduce several parametric assumptions and fix certain parameters that are otherwise difficult to estimate.

5.1 Parametric Assumptions and Normalizations

- Search Choices: the number of searches performed by buyers follows a Poisson distribution, $m_i^* \sim Poisson(\lambda)$. The share of buyers who choose to conduct single-homing in equilibrium is ω^*. I denote the set of all parameters to be estimated as $\Theta = \{\theta, \omega, \alpha, \lambda, \omega\}$. When buyers are allowed to have different quality preferences in the model, I obtain the following $\Theta = \{\theta^H, \theta^L, \sigma, \alpha, \lambda^H, \lambda^L, \omega^H, \omega^L\}$. I assume the distribution of WTP is the same before and after the merger, but the distribution of equilibrium search choices can change following the merger.

- Proportion of high/low-type buyers: based on the Texas data, I assume that $share^H = 0.6, share^L = 0.4$;[14]

- Ratio of Buyers to Sellers: I fix $\gamma = 4$ because the median number of bidders in auctions equals 4;

- I use 6%, 3%, and 5%, which are the weighted average of the observed commission rates, to approximate the commission rates charged by IP, RBA pre-merger, and RBA post-merger, respectively.

5.2 Algorithm

As shown in the identification section, I can first use the observed distribution of prices and bids to estimate the distribution of WTP and the distribution of equilibrium search choices. Then, the distribution of search costs can be estimated based on the estimated distributions. The estimation framework is summarized in the following two steps:

- ***Step 1*** I use a nested fixed-point algorithm to estimate the distribution of buyers' WTP and the distribution of buyers' search choice in equilibrium based on the observed bidding and transaction data.

[14]For the trucks transacted in all channels, the share of high type buyers is 0.6 and the share of low type buyers is 0.4. For the trucks transacted in auctions only, the share of high type buyers is 0.35 and the share of low type buyers is 0.65. In Appendix E.1, I show the estimation results using both pair of shares.

- ***Inner Loop*** I numerically solve the equilibrium bidding and auction entry strategies of buyers in the inner loop and generate the distribution of prices and the distribution of bids based on simulations.
- ***Outer loop*** I use the simulated distributions and observed distributions to construct several moments for estimation. The distribution of WTP and the distribution of equilibrium search choices are estimated in this outer loop.

- ***Step 2*** I use the estimated distribution of WTP and distribution of equilibrium search choices to nonparametrically estimate the distribution of search costs based on the equilibrium conditions for the equilibrium search strategies.

Next, I discuss the details in each step.

5.2.1 Solving Equilibrium Bidding and Auction Entry Strategies

When there are two types of buyers, there are four equilibrium payoff functions from auctions in each market: U_H^{IP*},U_L^{IP*},U_H^{RBA*} and U_L^{RBA*}. Since there is no analytical solution to this problem, I propose a numerical way to solve them. To implement the computational method, I assume that the expected payoff function from entering an auction is continuous in the quality of the goods.

Specifically, I use a two-dimension Lagrange interpolation (Judd [1998]) to approximate the equilibrium payoffs. Given the initial guess of the expected payoff functions $U^{(0)}$, I can figure out a set of simulated buyers' entry choices. Then I calculate a new expected payoff $U^{(1)}$ by averaging all the ex-post payoffs of buyers over simulations. A buyer's ex-post payoff from an auction is determined by the equilibrium bidding strategies and set of competitors in that auction. In Appendix D.1, I show the details of this computation procedure.

Given a guess of the distribution of WTP and equilibrium search choices, I can simulate a set of bids based on the equilibrium auction entry strategy and bidding strategy. To assign a price to the auctions with only one bidder, I assume that there is always an additional bidder in the auctions who mimics buyers' behavior. They draw WTP from buyers' distribution of WTP, bid truthfully, and discount their bids by the commission. The only difference is they do not make auction entry choices. We can treat these additional bids as bids from sellers or platforms to ensure trucks can be sold with a positive price when there is one buyer in the auctions.

Here I use 100 simulations and denote the sets of bids from simulations $\{\mathbf{b}^s(\Theta)\}_s$.

5.2.2 Estimating the Distributions of WTP and Equilibrium Search Choice

As shown in the identification part, the price distributions in markets with different sets of available trucks on each platform are used to identify the model. Using $\{\mathbf{b}^s(\Theta)\}_s$ and observed data, I can calculate the distribution of bids and the distribution of prices. Based on these distributions, I construct three sets of moments $\{g_1(\Theta), g_2(\Theta), g_3(\Theta)\}$. The estimator can minimize the Wald-type objective function:

$$\hat{\Theta} = argmin_{\Theta} \begin{pmatrix} g_1(\Theta) \\ g_2(\Theta) \\ g_3(\Theta) \end{pmatrix}' W \begin{pmatrix} g_1(\Theta) \\ g_2(\Theta) \\ g_3(\Theta) \end{pmatrix}$$

where W is the weighting matrix.

The underlying justification for using the first two sets of moments is that the differences between the simulated prices and observed prices of the trucks with the same quality on the same platform faced with the same set of available trucks are independent across auctions and having zero means. The underlying justification for using the third set of moments is that the differences between the simulated quality and observed quality for the trucks purchased by the same type of buyers on the same platform faced with the same set of available trucks are independent across auctions and having zero means.

First Set of Moments ($g_1(\Theta)$): Mean and Standard Deviation of Prices

First, I calculate the mean and standard deviation of the log(price) of IP/RBA before/after the merger. The simulated mean and standard deviation can be achieved by averaging all simulated price across all auctions and sets of available trucks on each platform pre- or post-merger. Using the observed data, I can calculate their correspondence in reality. I construct a set of moments to measure the difference between simulated data and observed data. For example, I consider the mean of the online transaction price pre-merger in the one-type model. The moment is calculated as follows

$$\frac{1}{K}\sum_{k=1}^{K}\frac{1}{N^k}\sum_{j=1}^{N^k}[\frac{1}{N^s}\sum_{s}(log(p_j^{IP,Pre,k,s})) - (log(\tilde{p}_j^{IP,Pre,k}))]$$

Here, market $1...K$ represents K realized sets of available trucks on each platform before the merger, N^s is the number of simulations, and $\tilde{p}$ are the observed prices in the data.

As shown above, the price distribution of trucks in different quality groups can differ. I divide the trucks into two categories according to whether the trucks' quality is above the median. In each category, I calculate the mean and standard deviation of the log(price). For the online auction after the merger, I also construct moments of the price distribution for auctions with one bidder in each auction.

Second Set of Moments ($g_2(\Theta)$): Relationship Among Price, Quality and Trucks Available on Each Platform

The first set of moments includes the aggregate information about price distributions. It is necessary to capture more information about price distributions at different quality levels and different realizations of available trucks. Since there are numerous quality levels and realized sets of available trucks, I use regressions to achieve this goal. Specifically, I regress the transaction price of trucks on the trucks' quality and some measurements of available trucks which are used in the data section. The measurements include the number of trucks available on each platform, average quality of other trucks available on the same platform and the average quality of trucks available on the other platform in the same market. I conduct regressions using both simulated data and observed data. For example, I consider the online transaction price as follows:

$$
\begin{aligned}
log(p_j^{IP,k,s}) =&\beta_0^{IP,s} + \beta_1^{IP,s} q_j^{IP,k,s} + \beta_2^{IP,s}(q_j^{IP,k,s})^2 + \beta_3^{IP,s}\overline{q}_{-j}^{IP,k,s} + \beta_4^{IP,s}\overline{q}^{RBA,k,s} + \ldots \\
&\beta_5^{IP,s} N^{IP,k,s} + \beta_6^{IP,s} N^{RBA,k,s} + \epsilon_j^{IP,k,s} \\
log(\tilde{p}_j^{IP,k}) =&\tilde{\beta}_0^{IP} + \tilde{\beta}_1^{IP} q_j^{IP,k} + \tilde{\beta}_2^{IP}(q_j^{IP,k})^2 + \tilde{\beta}_3^{IP}\overline{q}_{-j}^{IP,k} + \tilde{\beta}_4^{IP}\overline{q}^{RBA,k} + \ldots \\
&\tilde{\beta}_5^{IP} N^{IP,k} + \tilde{\beta}_6^{IP} N^{RBA,k} + \tilde{\epsilon}_j^{IP,k}
\end{aligned}
$$

Above are two regressions based on simulated data and observed data. I conduct the regressions for the pre-merger period and post-merger period, respectively. Since WTP is assumed to follow a log-normal distribution, I use log(price) instead of price itself. $\overline{q}_{-j}^{IP}$ is the average quality of trucks on IP except for truck j and $\overline{q}^{RBA}$ is the average quality of trucks on RBA in the same market. As I discussed before, the decrease of search cost will encourage buyers with high random values to enter the auctions with high-quality trucks, so I add a quadratic term of trucks' quality and calculate the price sensitivity to quality at the median and third quartile of quality. The coefficient of $\overline{q}^{RBA}$ can capture the cross-platform sensitivity emphasized before.

The moments are used to measure the difference in the relationships between the simulated data and observed data. I can attempt to match all the coefficients directly or match the difference in coefficients pre- and post-merger.

Third Set of Moments ($g_3(\Theta)$): Moments of Different Types of Buyers

The third set of moments is used to estimate the model with two types of buyers. According to the winners' types in auctions won by buyers in Texas, I can divide the data into two subsets. Different types of buyers have different quality preferences, which can result in different quality distributions and price distributions for trucks purchased by different types of buyers. The average quality $\overline{q}_T$ and the average price of $\overline{p}_T$ differ among the trucks in different subsets. The third set of moments is used to measure the difference between simulated data and observed data in these two measurements.

5.2.3 Search Cost

After obtaining the estimation results of the distribution of WTP and the distribution of equilibrium search choices, I use the equilibrium conditions mentioned in the model to nonparametrically estimate the bounds two distributions of search costs: $h^{mc}(\cdot)$ and $h^{fc}(\cdot)$.

I first calculate the average expected payoffs from all the possible deviations to other homing strategies and search frequencies, given other buyers follow the estimated equilibrium search. I assume buyers know the difference in distributions of available trucks on each platform pre-merger and post-merger. When calculating the expected payoffs from deviations pre-merger, I average all realized pre-merger markets in the data; when calculating the expected payoffs from deviations post-merger, I average all realized post-merger markets in the data. This assumption about buyers' belief is the same for the model with one type of buyers and the model with two types of buyers.

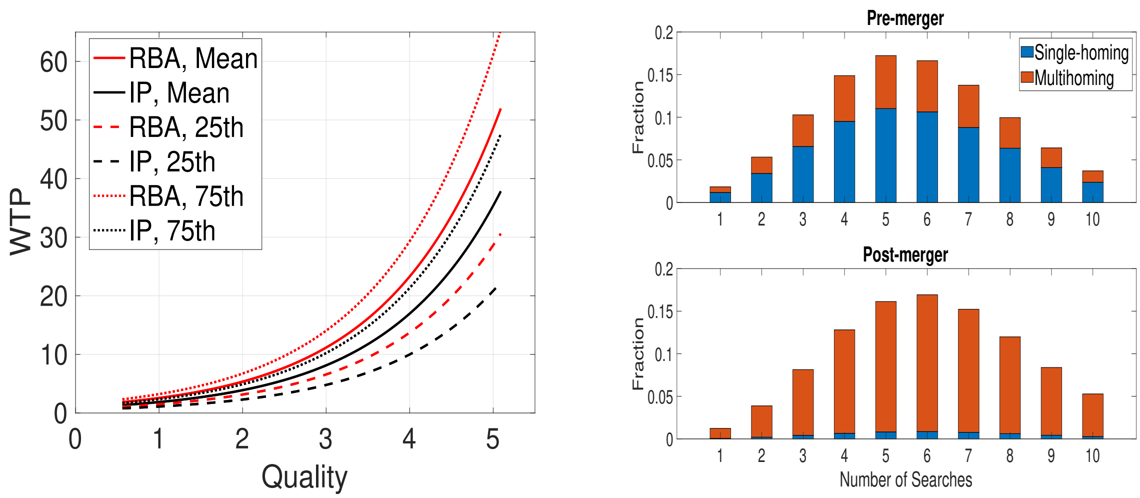
According to these results and the equilibrium conditions, I can construct a mapping from the distribution of equilibrium search choices to the joint distribution of search costs. The mapping has been shown in the identification part. Since a range of search costs can rationalize a search choice, I can only partially estimate search cost distribution. I denote the joint distribution of the lower bound of search costs as $H_{LB}^{fc,mc}$ and the joint distribution of the upper bound of search costs as $H_{UB}^{fc,mc}$. The corresponding marginal distributions of marginal cost and fixed cost can be calculated and are denoted $\{H_{LB}^{fc}, H_{LB}^{mc}\}$ and $\{H_{UB}^{fc}, H_{UB}^{mc}\}$. Similarly, I can partially estimate the distributions of search costs in a model with two types of buyers.

6 Estimation Results

6.1 Distribution of WTP and Distribution of Search Costs

Table 5 shows the estimation results of the one-type model. In the Appendix E.1, I show the estimation results for the two-type model under different assumptions about single-homing buyers' platform choice. Based on the estimation results, I can draw the implied average WTP, the 25th and 75th percentiles of WTP at different quality levels on different

Figure 8: Implied Distribution of WTP and distribution of equilibrium search choices



Notes: unit of WTP is $\$1,000$.

platforms (Figure 8). When $q = 3$, the average WTP is $\$8,135$ on IP and $\$11,172$ on RBA; when $q = 5$, the average WTP is $\$35,407$ on IP and $\$48,626$ on RBA . According to the way to construct the quality index, a truck's quality can decrease by two if increasing a truck's age from almost 0 to 15 years old.

Figure 8 also shows the implied distribution of search choices pre-merger and post-merger, where the number of searches is truncated at one and ten trucks. By comparing these two distributions, we see that buyers significantly increase the number of trucks to search. The median number of searches increased from 5 trucks to 6 trucks. More than 50% of buyers engage in multihoming, resulting in almost all buyers multihoming after the merger. This is consistent with the fact that the platform presents integrated search results as a default.

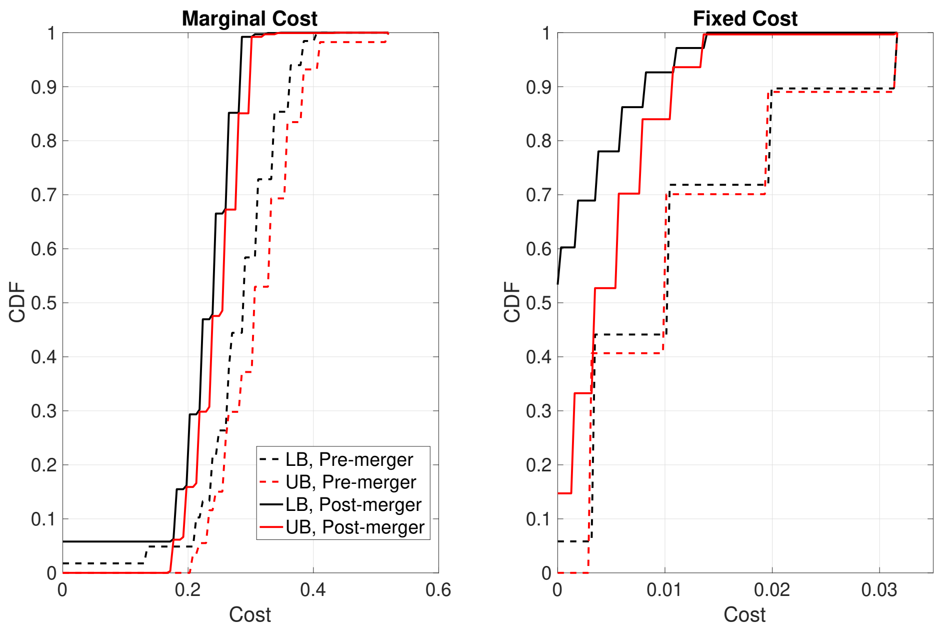
Given the estimated distribution of WTP, the change in buyers' equilibrium search choices results from the change in search costs. Using the approach mentioned in the estimation, I obtain the estimates of the distributions of search costs. Figure 9 shows the lower bound and upper bound of the cumulative distribution functions of search costs. The lower and upper bound of the median marginal search cost decrease from \$270 to \$224 and from \$328 to \$255, respectively. The lower and upper bound of the median fixed search cost decrease from \$4 to \$0 and from \$10 to \$5, respectively. The estimated costs of additional searches are quite high, but not unreasonable given that buyers need to conduct much searching before determining which trucks to buy. According to an investigation of the used truck market, on average, buyers spend approximately one day to finalize whether to purchase a truck. Considering that the average salary per hour in

Table 5: Estimation Results of the Model with One Type of Buyers

Quality Preference	
θ	0.7354
	(0.0027)
Distribution of v	
μ	0.0001
	(0.0205)
σ	0.6015
	(0.0064)
Discount of Quality Online	
α	-0.4314
	(0.0060)
Mean Number of Searches	
λ^{Pre}	5.7907
	(0.0721)
λ^{Post}	6.2964
	(0.0324)
Proportion of Buyers Single-Homing	
$\omega^{*,\text{Post}}$	0.0505
	(0.0134)
$\omega^{*,\text{Pre}}$	0.6392
	(0.0342)

Notes: standard errors are shown in parentheses. They are obtained by numerically calculating the derivatives in $(\frac{\partial g(\Theta)}{\partial\Theta} W \frac{\partial g(\Theta)}{\Theta})^{-1}$.

Figure 9: Cumulative Distribution Functions of Search Cost in the One-type Model

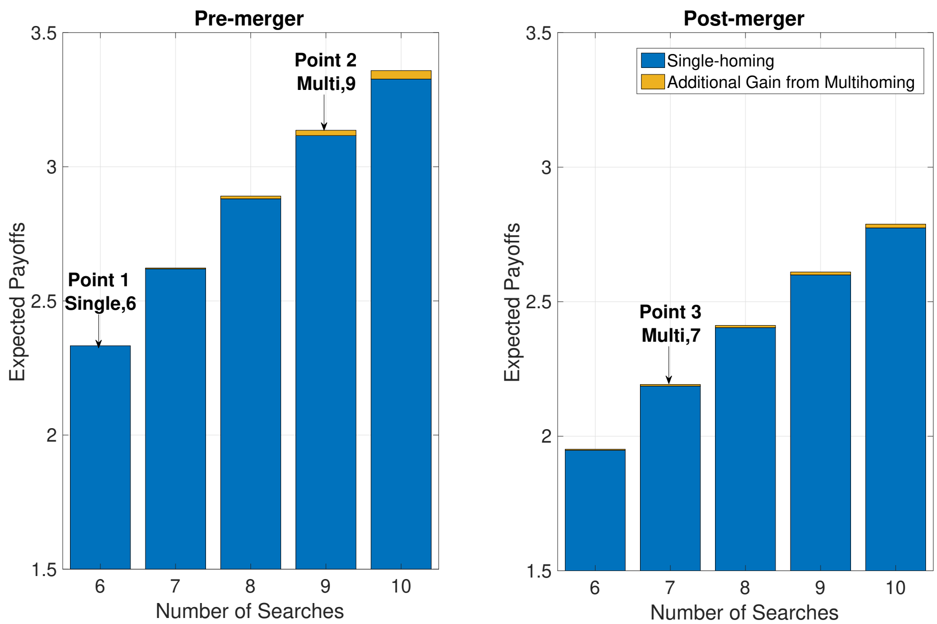


Notes: unit is $1,000.

the U.S. is approximate $30, the estimation results of the marginal costs are reasonable. One potential explanation for the lower marginal search costs after the merger is that the merged platforms design a better online environment for buyers to search and sales representatives are more familiar with the trucks in the market. This can help buyers to figure out their WTP of trucks with less effort. The estimated multihoming costs are small compared to the marginal costs. The magnitude of fixed costs depends on the assumption about the platform choice of single-homing buyers. I assume buyers know the realized number of trucks in the one-type model before they are randomly allocated to a platform. Therefore, the fixed costs of multihoming are mainly the costs of buyers becoming familiar with the system on these two platforms, the effort they take to register two accounts to monitor the trucks on different platforms, etc. Logically, these fixed costs are not very high. Additionally, the integrating policies provided by the merged platforms can lower these costs.

I use an example to illustrate how the change in search costs can change buyers' search choices. This example can also explain why the significant change in marginal search costs only leads to a small change in search frequency. Assume a buyer has $mc = \$317, fc = \$19$ pre-merger and $mc = \$239, fc = \$3$ post-merger. Her expected payoff functions are increasing and concave in the number of searches (Figure 10). When she searches more than six trucks, her expected payoffs under multihoming are higher than those under single-

Figure 10: How the Change in Search Costs Affects the Buyers' Search Choices



Notes: 1. unit is $\$1,000$; 2. 1-10 is single-homing, and 11-20 is multihoming.

homing. Given the pre-merger search costs, she will choose to conduct single-homing and search for six trucks to earn her expected payoff $\$2,333$.

Next, the buyers' search costs decrease to the post-merger level. If all other buyers still choose the same search choices, this buyer will search for nine trucks under multihoming (Point 2). However, because other buyers are more likely to have lower search costs post-merger, she expects that they will search more aggressively. Because of the strategic substitution of searching among buyers, her expected payoff function shifts downward. In the new equilibrium, she will choose to search for seven trucks on both platforms (Point 3). Compared with her original search, the lower search costs encourage her to search for more trucks on both platforms, which can be applied to other buyers. Thus, the change in the distribution of search costs can explain the estimated change in the distribution of search choices.

6.2 Model Fit and Sensitivity Analysis

Table A3 shows how the model and estimation results fit the targeted moments of the observed prices and bid distributions. In the model with two types of buyers, I show the moments when single-homing high-type buyers choose the offline platform and low-type single-homing buyers follow the random choice rule. The model can fit most of the first and second-order moments of price. Additionally, the estimated results can capture the changes pre-merger and post-merger and fit the quality of trucks purchased by different types of buyers.

Here I show some examples. The observed and simulated average price of offline trucks are $\$21,977$ and $\$22,646$ pre-merger and $\$21,542$ and $\$22,198$ post-merger, respectively. Both simulated and estimated prices decrease by approximately $\$450$. According to the observed data, if the average quality offline increases by one and the average quality online decreases by one, we can predict that the price of a truck sold online will decrease by 14% more post-merger than pre-merger; according to the simulated data, if the average quality offline increases by one while the online quality remains the same, I can predict that the price of a truck sold online will decrease by 14.6% more post-merger than pre-merger. Pre-merger, the average quality of online trucks purchased by low-type buyers is 3.09 pre-merger and 3.12 post-merger in the Texas data. According to the estimates of the two-type model, the average quality is 3.09 pre-merger and 3.15 post-merger.

In addition to the targeted moments, I use the bidding data online post-merger to show how the estimates fit. In Figure 11, I draw the CDF of the quality and price on IP according to the number of bidders in the auction (n). For $10 \geq n > 2$, I also divide the quality into two groups. I observe that except for the case $10 \geq n > 2, q \leq 3.5$, all other price and quality distributions fit well.

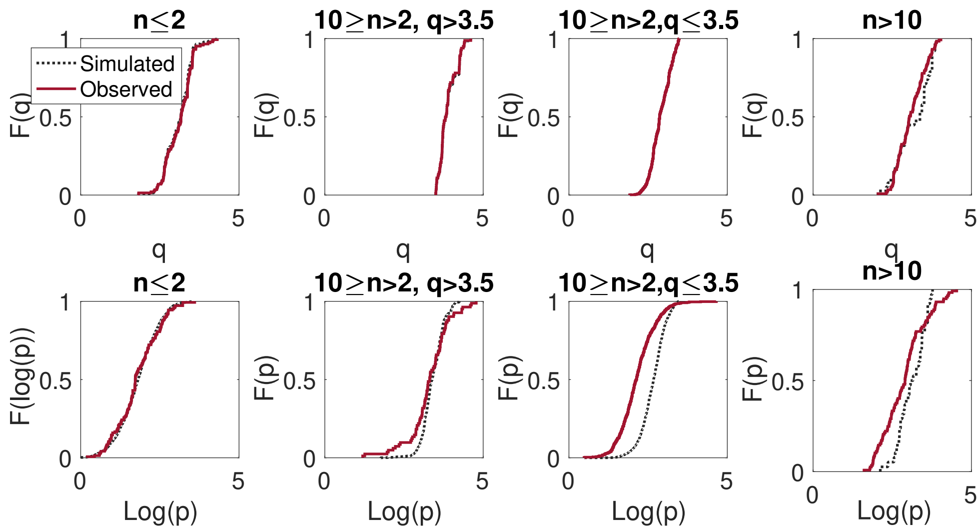
Finally, given the estimates, I can test how different moments can be used to identify different model primitives based on the approach proposed by Andrews et al. [2017]. I show the results in Appendix **??**. Consistent with the model, the parameters of the equilibrium search choices are sensitive to the moments describing how the transaction price is sensitive to the truck's quality and how it is sensitive to the average quality of trucks on the other platform.

7 Counterfactuals

7.1 Roadmap

As shown above, following the merger, I can observe three types of policy changes. In this section, I analyze each change individually. Here I briefly show the framework of each counterfactual.

Figure 11: Observed and Simulated Distributions of Quality and Price Online Post-merger



Notes: unit of price is $\$1,000$.

- The first change, which is also the focus of this paper, is the change in the buyers' search costs resulting from the change in the integration policies. In this counterfactual, all buyers are ex-ante symmetric. I control for the other two changes. Regarding the supply side, I assume that all observed changes are irrelevant to the merger; thus, when calculating the expected payoffs, I compute payoffs pre- and post-merger search costs across all observed markets; regarding the commission rate, I calculate the welfare change from lower search costs with pre-merger observed commission rates. Except for the estimated change in search costs, I also consider the case where there is a change only in marginal costs and the case there is a change only in fixed costs.

- The second change is the change in commission charged by the platforms and paid by buyers. To make the change affects buyers' search choices, I also consider cases where trucks are sold via auctions with reserve prices. I calculate the welfare under alternative changes in commission rates with one type of buyer and estimated search costs post-merger. In this counterfactual, I assume that all observed changes on the supply side are irrelevant to the merger.

- The final change is the change in sets of trucks available on each platform as follows: sellers with different quality levels list their trucks across platforms differently. Since this counterfactual focuses on qualities, I allow buyers to have two different preferences for quality. I calculate the welfare change from the change on supply side with estimated pre-merger and post-merger search costs separately. The commission rate used in this counterfactual is the same as that observed pre-merger. Considering the change in the general quality distribution may be irrelevant to the merger, I construct two new sets of available trucks in which both sets have the same population quality distribution and 64 markets. In the first set, the trucks are separated into different platforms according to the rule in the pre-merger data; in the second set, trucks are separated into different platforms according to the rule in the post-merger data.

Next, I discuss how welfare changes in each counterfactual.

7.2 Welfare Analysis with Changes in Search Costs

Efficiency Gain Given the estimated search costs of buyers pre- and post-merger, I first re-calculate buyers' equilibrium search choices under different cost structures. In the estimation part, I have estimated the thresholds of search costs for buyers to choose different search choices. Here, I assume that the search costs following uniform distributions whose supports are defined by these these thresholds. Given the distributions of search costs, I can solve for new equilibrium search choices which allow buyers to choose different number of trucks to search under different homing choices. The details of the algorithm used to solve the new equilibrium is shown in the Appendix F.1. As mentioned above, I control for the change on the supply side by assuming that the possible sets of trucks available on each platform include all realized markets. Table 6 shows the results.

Buyers tend to search more trucks under multihoming. When their fixed search costs become lower, buyers are more likely to choose multihoming. When their marginal search costs are lower, buyers tend to search more trucks no matter which homing choice they choose.

Table 6: New Equilibrium Under Alternative Changes in Search Costs

mc	Pre		Post	
fc	Pre	Post	Pre	Post
Mean Number of Searches				
λ^{Single}	4.78	3.43	5.79	4.01
λ^{Multi}	6.66	6.80	7.46	7.35
Proportion of Single-homing				
ω^*	0.62	0.34	0.60	0.20

Notes: "Pre" means pre-merger, "Post" means post-merger, "mc" means marginal search costs, and "fc" means the fixed search costs for multihoming.

Next, I calculate the welfare under alternative changes in the search costs. Table 7 compares welfare under different cost structures. The search costs of buyers are between

$23.9 million and $32.2 million and total surplus is between $231.6 million and $239.9 million when the search costs follow pre-merger distributions (see the second column in the table). Changes in both the marginal and fixed search costs can result in higher trading surplus and total surplus. Welfare increases more significantly than when only one type of search costs are lowered. Comparing the cost structure pre-merger and post-merger shows that the total trading surplus increases by approximately 6% on average, and the total surplus increase by 8% to 18%. The total surplus of buyers and sellers also increases from [$217.3 million,$225.6 million] to [$245.5 million,$260.1 million]. Among these gains, sellers' welfare gain is derived from higher trading surplus, and buyers' welfare gain comes from lower search costs. Buyers' surplus from trading is lower post-merger.

Table 7: Welfare Under Alternative Changes in Search Costs

mc	Pre		Post	
fc	Pre	Post	Pre	Post
Buyers	[18.8,31.7]	[18.3,32.8]	[31.0,44.8]	[31.0,45.4]
Trading	132.6	132.6	130.03	130.0
Search Cost	[100.9,113.8]	[99.8,114.2]	[85.2,99.0]	[84.6,99.0]
Sellers	175.9	179.8	189.9	190.5
Platform	14.5	14.6	15.0	15.0
IP	3.1	3.1	3.2	3.2
RBA	11.4	11.5	11.8	11.9
Total Trading	323.0	324.5	334.9	335.5
Total Surplus	[209.2,222.1]	[210.2,224.7]	[235.9,249.7]	[236.5,250.9]

Notes: 1. unit is $1,000,000; 2. "Search Cost" includes the total search costs generated by all buyers in the market regardless of whether the buyers win the auctions. 3. Sellers' surplus is adjusted by their possible WTP, namely, I randomly draw the WTP of sellers from the distribution of buyers' WTP. For the auctions online, sellers' WTP also has a discount α; 4."Pre" means pre-merger, "Post" means post-merger.

To explain the observed welfare change, I calculate the average trading surplus of buyers and sellers from choosing trucks at different quality levels on different platforms (Table 8). It can be observed that, in general, buyers obtain a lower average surplus from high-quality trucks post-merger. This is especially true for RBA who has a larger market share and relatively more high-quality trucks in the data. With more searches under multihoming, buyers access more information about trucks across platforms before they make auction entry choices on both platforms. As the economics of search choice shows, more buyers with high idiosyncratic values choose the auctions with high-quality trucks and choose the platform that includes those auctions. Therefore, buyers are less likely to win those auctions or pay more to win the auctions. This situation also results in sellers with high-quality trucks obtaining higher surplus. Combined with the increased revenue of platforms, the average surplus from trading is higher post-merger, and the increase is more significant in the auctions with high-quality trucks. This finding is consistent with the economics of search cost analysis mentioned in the model part: when buyers search more trucks under multihoming, it can achieve more assortative matching results across platforms.

7.3 Welfare Analysis with Changes in Commission

The merger's main concern is that the merger can increase the market power such that users of the platforms may be harmed. While a larger share of the surplus is transferred from sellers to platforms because of the increased commission rate, sellers also benefit from buyers' search choice change. At least, this situation is true for sellers with high-quality trucks. However, if the change in price policy can generate a counter-search effect, it may partially offset the efficiency gain from lowering search costs.

When the platforms charge the observed higher commission rate from buyers post-merger, the change will not alter buyers' search choices because in the second-price auctions with no reserve price, buyers can completely transfer the burden of commission to sellers by shading their bids if entry choices of sellers are exogenous. Resolving the equilibrium with or without the change in commission shows that buyers' equilibrium search choices keep the same (Table 9). The change only affects the welfare split between sellers and platforms (Table 10). The platform obtains a larger share of surplus post-merger (from \$15.0 million to \$22.5 million); of this share, approximately \$7.5 million is transferred from sellers to the merged platforms because of the increase in commission on RBA. Given the supply side fixed, the total surplus of buyers and sellers post-merger outweighs the one pre-merger with the observed change in commission rate and estimated change in search costs.

Considering that in reality, some auction platforms, such as eBay, use reserve prices, I construct a counterfactual in which sellers set reserve prices in their auctions. The reserve prices equal the sellers' potential WTP. Then, since buyers cannot completely transfer the burden of commission to sellers by lowering their bids, the change in commission can affect buyers' entry and search choices.

Instead of using the approximation of post-merger commission structure, i.e., 6% for IP and 5% for RBA, I consider alternative higher commission rates. The additional reserve price with high commission works as an additional competitor for all buyers, and the reserve prices are higher for auctions with high-quality trucks. Thus, these commission fees lower buyers' expected payoffs from extensive searching. Some buyers deviate from the original search choices to search for fewer trucks and conduct single-homing. The average equilibrium search frequency will become lower, and the share of single-homing buyers will increase. For example, when the commission rate increases to 50%, the average number of search decreases from 6.86 to 6.11, and the share of single-homing buyers increases from 24% to 33% (see Table 9).

Table 8: Average Trading Surplus and Split at Different Quality Levels (1)

	$q \in [1, 3]$			$q \in (3, 3.5]$			$q \in (3.5, 5]$		
Search Costs	Pre	Post	Δ	Pre	Post	Δ	Pre	Post	Δ
Total									
IP	8.63	9.02	**0.36**	13.44	14.02	**0.58**	22.29	23.34	**1.05**
RBA	11.87	12.62	**0.75**	18.79	20.12	**1.33**	29.32	31.37	**2.05**
Buyers									
IP	3.69	3.71	**0.02**	5.43	5.38	**-0.05**	8.35	8.12	**-0.23**
RBA	5.04	4.96	**-0.06**	7.58	7.39	**-0.19**	11.01	10.57	**-0.44**
Sellers									
IP	4.31	4.67	**0.36**	7.04	7.63	**0.59**	12.31	13.52	**1.21**
RBA	6.38	6.79	**0.41**	10.50	11.29	**0.79**	17.21	18.57	**1.36**
Platforms									
IP	0.63	0.64	**0.01**	0.97	1.01	**0.04**	1.63	1.70	**0.07**
RBA	0.45	0.87	**0.35**	0.71	1.44	**0.58**	1.10	2.23	**0.90**

Notes: 1. unit is \$1,000; 2. Here, buyers trading surplus on IP means the average trading surplus of winners from auctions on IP; 3. The difference Δ with darker color shows larger number.

When platforms charge buyers a commission rate as high as 70% (see the last column in Table 9 and Table 10), buyers' average search frequency will decrease to 5.75. The share of single-homing buyers is approximately 39%. The surplus from trading will decrease from that post-merger ($360.3 million) to a much lower value ($342.0 million) close to the one pre-merger.

Table 9: New Equilibrium Under Reserve Prices and Alternative Changes in Commission Rates

Search Costs	Pre	Post		
Reserve Price	No	No	Yes	No
Commission Rate of IP	3%	10.88%	10.45%	5%
Mean Number of Searches				
λ^{Single}	4.78	3.43	3.83	4.01
λ^{Multi}	6.60	6.80	7.30	7.35
Share of Single-homing				
ω^*	0.62	0.34	0.22	0.20

Notes: "RP" means the case with the reserved price.

Table 10: Welfare Under Reserve Price and Alternative Changes in Commission Rates

Search Costs	Pre	Post		
Reserve Price	No	No	Yes	No
Commission Rate of IP	3%	10.88%	10.45%	5%
Buyers Trading	132.6	127.5	125.8	129.4
UB of Search Cost	100.9	84.6	84.5	84.6
Sellers	175.9	164.7	166.3	183.5
UB of Buyers' and Sellers' Surplus	207.6	207.6	207.6	228.3
Platform	14.5	43.3	41.9	22.6
UB of Total Surplus	222.1	250.9	249.5	250.9

Notes: 1. "RP" means the case with reserved price and I solve for commission fees which eliminate the welfare gain from lowering search costs; 2. unit is $1,000,000; 3. "Search Cost" includes the total search costs generated by all buyers in the market regardless of whether the buyers win the auctions. 4. Sellers' surplus is adjusted by their possible WTP, namely, I randomly draw the WTP of sellers from the distribution of buyers' WTP. For the auctions online, sellers' WTP also has a discount α; 5. "Pre" means "Pre-merger" and "Post" means "Post-merger"

In summary, the increased market power may allow the merged platforms to charge a higher commission rate, which can discourage buyers from searching for more trucks on two platforms when they cannot completely transfer the burden to sellers. This will result in a lower total trading surplus. However, at least in this auction setting, the platform needs to charge a higher commission rate to eliminate the welfare gain from lower search costs with the supply fixed. Therefore, when analyzing this merger, if the platform can significantly lower the market's search costs, the efficiency gain from integrating policies can be substantial.

7.4 Welfare Analysis with Changes in Supply Side

In the data section, I show that sellers with different quality trucks may enter platforms according to a different rule after the merger: sellers with high-quality trucks are more likely to list offline, and sellers with low-quality trucks tend to list online. If buyers are ex-ante asymmetric, having different quality and platform preferences, are there any benefits from separating sellers by quality into two different platforms in the observed way? This counterfactual attempts to investigate this issue. As mentioned above, I use two new data sets that follow different rules to separate the trucks into auctions. Then I compute the predicted outcomes in each market based on these two data sets with pre-merger and post-merger search costs.

Table 11 shows the new equilibrium search choices of buyers under alternative changes. First, regardless of whether pre-merger or post-merger search costs are applied, high-type buyers search for more trucks and tend to single-home when trucks are separated into platforms in the way post-merger. It is because high-type buyers can easily target high-quality trucks by single-homing. The change is more significant when the search costs of multihoming are high since, in that case, buyers cannot easily access the trucks on other platforms and highly count on the composition of trucks on their single-homed platform. Second, faced with fiercer competition from high-type buyers in the offline auctions with high-quality trucks, low-type buyers tend to search for fewer trucks if the search costs are the same. Finally, similar to the one-type model, lower search costs can trigger both types of buyers to search for more trucks and conduct multihoming.

Table 11: New Equilibrium Under Alternative Changes in Supply Side

Search Costs	Pre		Post	
Supply Side	Pre	Post	Pre	Post
Mean Number of Searches				
$\lambda^{H,\text{Single}}$	6.27	7,42	6.78	8.05
$\lambda^{H,\text{Multi}}$	8.16	8.07	7.42	6.17
$\lambda^{L,\text{Single}}$	3.04	2.97	5.83	4.06
$\lambda^{L,\text{Multi}}$	5.66	5.98	5.72	5.54
Share of Single-homing				
ω^{H*}	0.51	0.70	0.35	0.57
ω^{L*}	0.49	0.54	0.16	0.17

Notes: "Pre" means pre-merger, "Post" means post-merger.

Table 12 shows the welfare of different groups. Both the change in the supply side and lower search costs can increase the total trading surplus. Specifically, the change in the supply side alone can increase the trading surplus by 4.2%. The supply-side change significantly increases the trading surplus offline and RBA's revenue. This change is more remarkable when the search costs are high. High-type buyers benefit from this change, but low-type buyers get a lower trading surplus because high-type buyers search more aggressively. The lower search costs post-merger can reduce the loss of low-type buyers. Also, with lower search costs, the surplus of online sellers and IP increases significantly.

Table 12: Welfare Under Alternative Changes in Supply Side

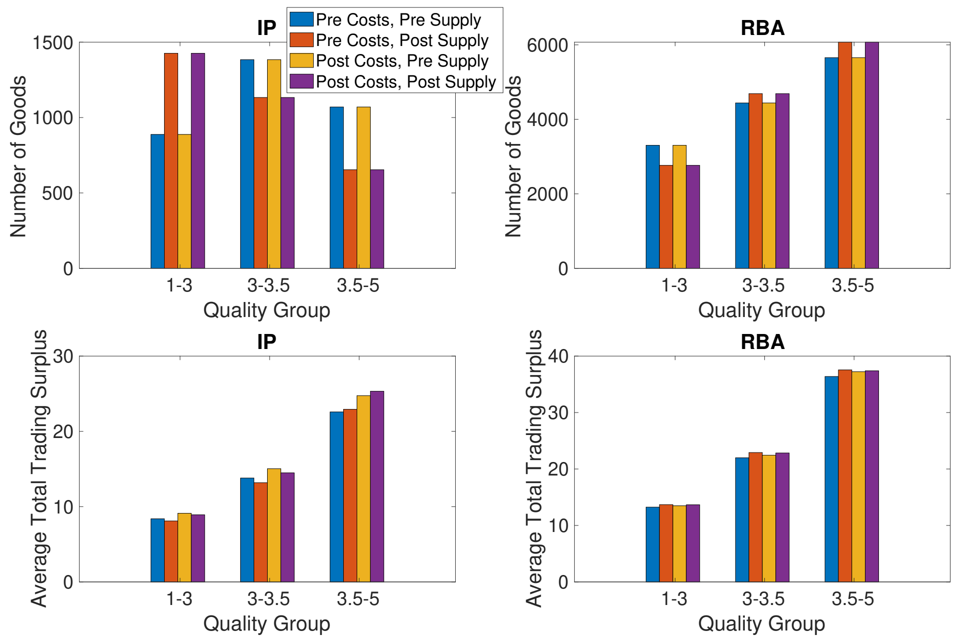
Search Costs	Pre		Post	
Supply Side	Pre	Post	Pre	Post
High Type	88.2	84.4	82.2	90.4
Low Type	29.3	33.0	33.7	28.5
Search Cost	[78.0 88.6]	[58.3 65.9]	[60.6 67.8]	[76.2 87.9]
Total Buyers	[28.9 39.5]	[51.5 59.1]	[48.1 55.4]	[31.1 42.8]
Sellers	183.7	192.5	194.1	187.9
Sellers IP	26.2	21.6	26.4	22.1
Sellers RBA	157.5	170.9	167.7	165.9
Platform	25.0	25.7	25.7	25.3
IP	3.7	3.1	3.7	3.1
RBA	21.3	22.6	22.0	22.2
Total Trading	326.1	335.5	335.7	332.3
Total Surplus	[237.5 248.2]	[269.6 277.2]	[267.9 275.1]	[244.4 256.1]

Notes: 1. unit is $1,000,000; 2. "Search Cost" includes the total search costs generated by all buyers in the market, regardless of whether the buyers win the auctions. 3. Sellers' surplus is adjusted by their possible WTP, namely, I randomly draw the WTP of sellers from the distribution of buyers' WTP. For the auctions online, sellers' WTP also has a discount α; 4. "Pre" means pre-merger, "Post" means post-merger.

Similarly, to determine the reason for the changes in welfare, I calculate the average trading surplus of the different groups at different quality levels under different cases (Table 13 and Figure 12). The numbers of trucks in the different groups change when separating trucks according to different rules. When it comes to the average trading surplus, except for the high-quality group online, the post-merger rule on the supply side lower the surplus online and increase the surplus offline because online trucks are less likely to be searched by buyers. However, since the number of high-quality offline trucks increases, the total trading surplus significantly increases in Table 12.

If the platforms can lower the search costs, some high-type buyers will shift to multi-homing and enter online auctions if they are more likely to win those auctions, and some low-type buyers will search more aggressively. The trading surplus from online auctions can notably increase while the trading surplus from offline auctions slightly decreases. The decrease in search costs is more beneficial for the markets with a small number of offline auctions. To be specific, Figure 13 illustrates that, in the markets where $\frac{N^{IP}}{N^{RBA}}$ is large, the case with the post-merger costs can generate a significantly higher average trading sur-

Figure 12: Number of trucks and Average Trading Surplus in Different Quality Groups



Notes: unit of Average Trading Surplus is $\$1,000$.

plus than the case with the pre-merger costs. Therefore, combining the change in search costs with the change in the number of trucks can considerably increase the total trading surplus.

8 Discussion

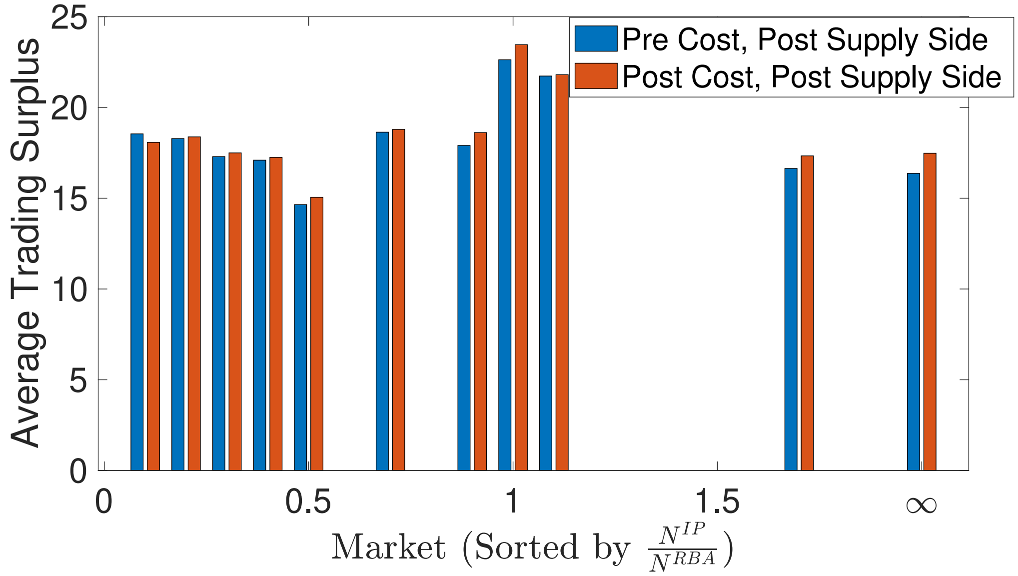
As mentioned many times in the paper, the current paper focuses on the buyers' search behavior and discusses the welfare effect of the merger through altering buyers' search costs. Ideally, we should endogenize both buyers' and sellers' entry decisions to the platform. Although this can provide a complete picture of all the participants in the market, it requires more data and significantly raises the computation burden. In this section, I will discuss the situation where I relax the exogenous supply assumption. While I still treat the buyers' platform entry exogenous, buyers' search choice now will be affected by sellers' platform entry strategy. Therefore, I can partially capture the indirect network effect in

Table 13: Average Trading Surplus and Its Split at Different Quality Levels (2)

	$q \in [1,3]$				$q \in (3,3.5]$				$q \in (3.5,5]$			
Search Costs	Pre		Post		Pre		Post		Pre		Post	
Supply Side	Pre	Post	Pre	Post	Pre	Post	Pre	Post	Pre	Post	Pre	Post
Number of trucks												
IP	888	1,426	888	1,426	1,384	1,133	1,384	1,133	1,070	654	1,070	654
RBA	3,303	2,765	3,303	2,765	4,440	4,691	4,440	4,691	5,661	6,073	5,661	6,073
Average Surplus												
Total												
IP	8.38	8.10	9.12	8.92	13.80	13.18	15.04	14.49	22.58	22.93	24.75	25.33
RBA	13.25	13.69	13.49	13.67	21.99	22.92	22.45	22.84	36.39	37.55	37.24	37.39
Buyers												
IP	3.75	3.73	3.83	3.75	5.91	5.78	5.94	5.74	9.04	9.34	9.00	9.19
RBA	4.88	4.90	4.90	4.92	7.71	7.71	7.65	7.71	11.68	11.56	11.54	11.52
Sellers												
IP	4.01	3.76	4.62	4.52	6.90	6.46	8.04	7.73	11.94	11.97	14.01	14.37
RBA	7.43	7.82	7.63	7.78	12.74	13.62	13.24	13.55	22.20	23.42	23.14	23.31
Platforms												
IP	0.62	0.60	0.66	0.65	1.00	0.95	1.07	1.03	1.60	1.63	1.74	1.77
RBA	0.94	0.97	0.95	0.97	1.53	1.59	1.56	1.58	2.50	2.57	2.56	2.57

Notes: 1."Pre" means pre-merger, "Post" means post-merger. 2. unit is \$1,000; 3. Sellers' surplus is adjusted by their possible WTP; Namely, I randomly draw the WTP of sellers from the distribution of buyers' WTP. For the auctions online, sellers' WTP also has a discount α.

Figure 13: Average Trading Surplus in Different Markets



Notes: 1. unit of Average Trading Surplus is $\$1,000$; 2. the share of $\frac{N^{IP}}{N^{RBA}}$ is round to 0.1; 3. for the markets without offline auctions, $\frac{N^{IP}}{N^{RBA}} = \infty$.

this two-sided platform market: a buyer's search choice is indirectly affected by other buyers' search choices through their effect on sellers' platform entry. Following, I will discuss two cases according to the data availability of transacted trucks in the market outside of these two auction platforms.

Ideally, I can collect the number of trucks with different quality levels on each platform, including the outside market. Given more complete data, I can endogenize sellers' entry to the merged platforms. In this case, a buyer's search choice is also indirectly affected by other buyers' search choices through its effect on the aggregate number and quality of sellers on these two platforms. Similar to the game mentioned above, there is an additional stage describing sellers' endogenous strategy. However, now sellers make their choices among three options: platform A, platform B, and the outside market. Still, I assume the number and quality of trucks that appear in a market are given. Figure 14 shows the new timeline.

Now sellers' three entry costs are drawn from common distributions $F^{A,\epsilon}(\cdot)$, $F^{B,\epsilon}(\cdot)$ and $F^{O,\epsilon}(\cdot$. The realized supply on different platforms, including in the outside market, is still determined by the realized number of trucks in that market, their quality, and sellers' platform choices. Assume the trucks in the outside market can be sold by giving take-it-or-leave-it offers where a realized price of a truck with quality q_j is $exp(\theta_0 q + v_0)$ and

Figure 14: Timeline of the Game With Endogenous Platform Entry of Sellers (2)

$v_0 \sim N(\mu_0, \sigma_0^2)$. Assume there is always enough potential buyers in the outside market to accept a seller's offer no matter how many other sellers choose the outside option. Then, $V_S^O(q_j, \epsilon_j^O) = E[exp(\theta_0 q_j + v_0)] - \epsilon_j^O$. When sellers make platform choices, they need to compare V_S^A, V_S^B, and V_S^O. In equilibrium, a seller's equilibrium expected payoffs from entering platform A and B are functions of the private (q_j, ϵ_j^A) and (q_j, ϵ_j^B) respectively.

I can solve the equilibrium choice probabilities $Pr^A(q)$, $Pr^B(q)$ and $Pr^O(q)$. Then the elasticities of entry to the quality of trucks can be calculated. For example, $elas^A = \frac{\frac{\partial Pr^A(q)}{Pr^A(q)}}{\frac{\partial q}{q}}$. Without estimating the entire model with endogenous sellers, I will first use pre-merger markets to calculate $elas^A$, $elas^B$, and $elas^O$ in the data. These elasticities can be used to calibrate the model primitives in the outside option, given the distribution of search costs pre-merger. Next, I will simulate the market outcome when buyers draw lower search costs to check how sellers' entry choices are affected.

There are two ways to define the outside market. One is considering all the other channels and other auction platforms as the outside market. Then I can use the data from some states[15], which includes transaction data in all channels, to calculate a reasonable approx-

[15] Transaction data through all channels in Texas and Washington State is collected.

imation of elasticities and calibrate the model primitives in the outside market. Then I can simulate potential realizations of markets based on the nationwide transaction data in each month and census data of truck inventories in each state. In the nationwide transaction data, I know the number and average quality of trucks transacted each month. In the census data, I have the number of truck inventories in each state. Assuming the turnover rates of trucks are stable across states, I can simulate the number of transacted trucks in each state. Another way is only treating other auction platforms as the outside market. From some websites, such as Truckpaper.com, that collect trucks transacted through different platforms, I have collected data about nationwide trucks transacted pre-merger and post-merger on the other auction platforms. Although this data set might be incomplete, I can still use them to approximate some realized markets, including transactions in the outside market.

9 Conclusion

Using a recent merger case in the U.S. used heavy-truck auction market, this paper investigates how partially integrating two competing platforms can affect market outcomes and social welfare. To clearly analyze the causal effect, I develop a detailed model of buyers' behavior. Based on the model, this paper provides several predictions regarding the market outcome when the search costs are low. To quantify the welfare effect, I structurally estimate the distribution of WTP and distributions of search costs before and after the merger. The estimation results show a significant decrease in the search costs after the merger and reveal that buyers search more extensively across the platforms.

In the counterfactual part, I compare the welfare in the market with and without the change in search costs and observed commission. Buyers' more aggressive search allows them to access more information about the trucks before making auction entry choices. The trading surplus increases with the estimated distributions. While sellers with high-quality trucks always benefit from the change, other participants' welfare is more complicated. For example, buyers' welfare depends on the composition of competitors and the magnitude of the reduced search costs. The cost decomposition shows, lowering the search costs of multihoming can generate efficiency gain. When buyers search more extensively, the decentralized market's allocation results are close to those of a market with a centralized mechanism in which there is no coordination failure among buyers. I also combine the change in search costs with the following two alternative changes: high commission fees when auctions have reserve prices and separation of trucks into platforms according to their quality levels. The analysis shows that (1) the increased commission fees may discourage buyers from extensive searching when buyers cannot completely transfer the burden of commission to sellers; (2) the changes on the supply side may generate additional efficiency gain when considering single-homing buyers' platform preference.

Methodologically, the paper considers the heterogeneity among the participants in many dimensions. Both buyers and trucks are differentiated horizontally and vertically. Building upon the literature, I develop a new model that combines search and endogenous auction entry stages. The model can capture a wide range of transaction markets in which search costs are considerable.

Partial integration or the facilitation of multihoming is a common feature of platform mergers, and my analysis suggests that the welfare benefits may be substantial. To the extent that it is not easy for firms to facilitate multihoming prior to mergers, in the language of the Horizontal Merger Guidelines, these benefits are cognizable efficiencies that could be set against market power created by a merger. In the context of this merger, the benefits to buyers and sellers exceeded the harm caused by the increase in commission fees that followed the merger.

This paper can be extended in several ways. Besides extending the model by endogenizing sellers' platform entry, as discussed above, I will also consider some alternative changes along with the merger. For example, upon the acquisition, RBA forms a strategic alliance with Caterpillar. How this change will affect social welfare is another interesting topic to analyze.

References

Victor Aguirregabiria and Pedro Mira. Sequential estimation of dynamic discrete games. *Econometrica*, 75(1):1–53, 2007.

Jason Allen, Robert Clark, and Jean-François Houde. The effect of mergers in search markets: Evidence from the canadian mortgage industry. *American Economic Review*, 104(10):3365–96, 2014.

Isaiah Andrews, Matthew Gentzkow, and Jesse M Shapiro. Measuring the sensitivity of parameter estimates to estimation moments. *The Quarterly Journal of Economics*, 132 (4):1553–1592, 2017.

Elena Argentesi and Lapo Filistrucchi. Estimating market power in a two-sided market: The case of newspapers. *Journal of Applied Econometrics*, 22(7):1247–1266, 2007.

Mark Armstrong. Competition in two-sided markets. *The RAND Journal of Economics*, 37 (3):668–691, 2006.

Mark Armstrong and Julian Wright. Two-sided markets, competitive bottlenecks and exclusive contracts. *Economic Theory*, 32(2):353–380, 2007.

Nick Arnosti, Ramesh Johari, and Yash Kanoria. Managing congestion in decentralized matching markets. In *Proceedings of the fifteenth ACM conference on Economics and computation*, pages 451–451, 2014.

Susan Athey, Jonathan Levin, and Enrique Seira. Comparing open and sealed bid auctions: Evidence from timber auctions. *The Quarterly Journal of Economics*, 126(1):207–257, 2011.

David Bardey and Jean-Charles Rochet. Competition among health plans: A two-sided market approach. *Journal of Economics & Management Strategy*, 19(2):435–451, 2010.

Aaron Bodoh-Creed, Joern Boehnke, and Brent Richard Hickman. How efficient are decentralized auction platforms? *Becker Friedman Institute for Research in Economics Working Paper*, (2016-22), 2016.

Bernard Caillaud and Bruno Jullien. Chicken & egg: Competition among intermediation service providers. *RAND journal of Economics*, pages 309–328, 2003.

HA David. Augmented order statistics and the biasing effect of outliers. *Statistics & probability letters*, 36(2):199–204, 1997.

Babur De los Santos, Ali Hortaçsu, and Matthijs R Wildenbeest. Testing models of consumer search using data on web browsing and purchasing behavior. *American economic review*, 102(6):2955–80, 2012.

Andrey Fradkin. Search, matching, and the role of digital marketplace design in enabling trade: Evidence from airbnb. *Matching, and the Role of Digital Marketplace Design in Enabling Trade: Evidence from Airbnb (March 21, 2017)*, 2017.

Ali Hortaçsu and Chad Syverson. Product differentiation, search costs, and competition in the mutual fund industry: A case study of s&p 500 index funds. *The Quarterly Journal of Economics*, 119(2):403–456, 2004.

John J Horton. Buyer uncertainty about seller capacity: Causes, consequences, and a partial solution. *Management Science*, 65(8):3518–3540, 2019.

Przemysław Jeziorski. Estimation of cost efficiencies from mergers: Application to us radio. *The RAND Journal of Economics*, 45(4):816–846, 2014.

Kenneth Judd. Numerical methods in economics. Technical report, The MIT Press, 1998.

Elena Krasnokutskaya, Kyungchul Song, and Xun Tang. The role of quality in internet service markets. *Journal of Political Economy*, 128(1):75–117, 2020.

Jean-Jacques Laffont, Herve Ossard, and Quang Vuong. Econometrics of first-price auctions. *Econometrica: Journal of the Econometric Society*, pages 953–980, 1995.

Dan Levin and James L Smith. Equilibrium in auctions with entry. *The American Economic Review*, pages 585–599, 1994.

Marleen Marra et al. Pricing and fees in auction platforms with two-sided entry. Technical report, Sciences Po Departement of Economics, 2019.

Jean-Charles Rochet and Jean Tirole. Platform competition in two-sided markets. *Journal of the european economic association*, 1(4):990–1029, 2003.

Jean-Charles Rochet and Jean Tirole. Two-sided markets: a progress report. *The RAND journal of economics*, 37(3):645–667, 2006.

Marc Rysman. Competition between networks: A study of the market for yellow pages. *The Review of Economic Studies*, 71(2):483–512, 2004.

Tobias Salz. Intermediation and competition in search markets: An empirical case study. Technical report, National Bureau of Economic Research, 2020.

William F Samuelson. Competitive bidding with entry costs. *Economics letters*, 17(1-2): 53–57, 1985.

Katja Seim. An empirical model of firm entry with endogenous product-type choices. *The RAND Journal of Economics*, 37(3):619–640, 2006.

Gabriel Y Weintraub, C Lanier Benkard, and Benjamin Van Roy. Computational methods for oblivious equilibrium. *Operations research*, 58(4-part-2):1247–1265, 2010.

E Glen Weyl. A price theory of multi-sided platforms. *American Economic Review*, 100(4): 1642–72, 2010.

Appendix

A Supplement to Market and Data

A.1 Market

Figure A1 shows two examples of truck tractors. Figure A2 shows an example of the webpages of RBA pre-merger and Post-merger.

Figure A1: Pictures of Truck Tractors

Figure A2: Web Pages of RBA in 2016 and 2018

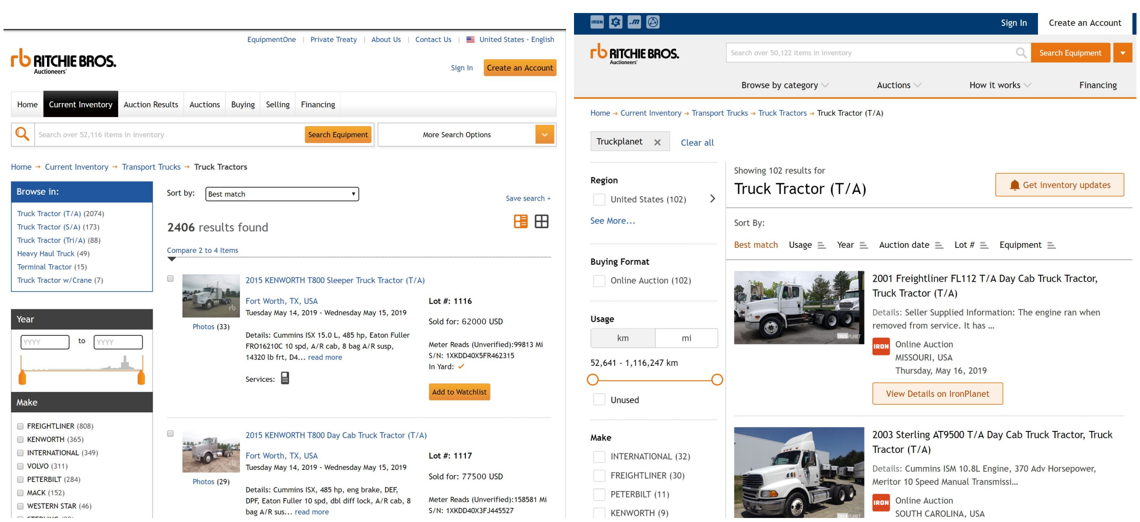
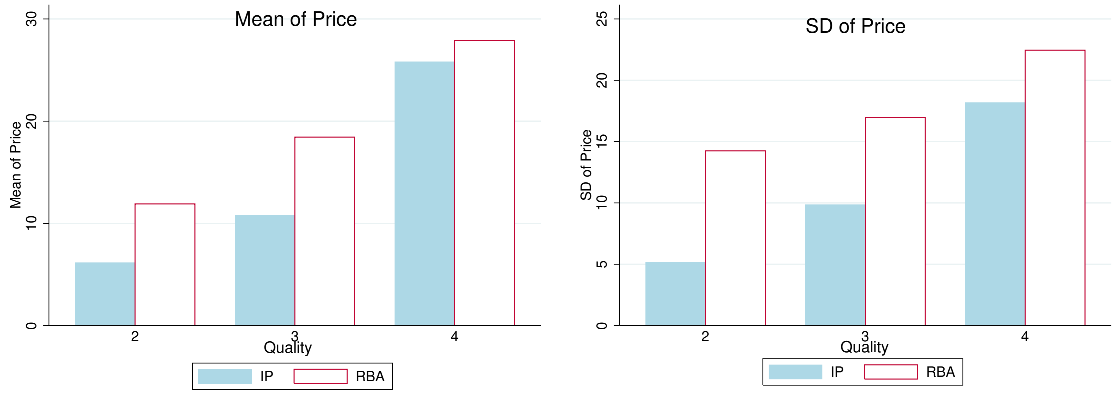


Figure A3: Price Distribution Across Platforms



Notes: 1. unit of Price is \$1,000; 2. Quality is round to the nearest integers.

A.2 Cross-sectional Variation

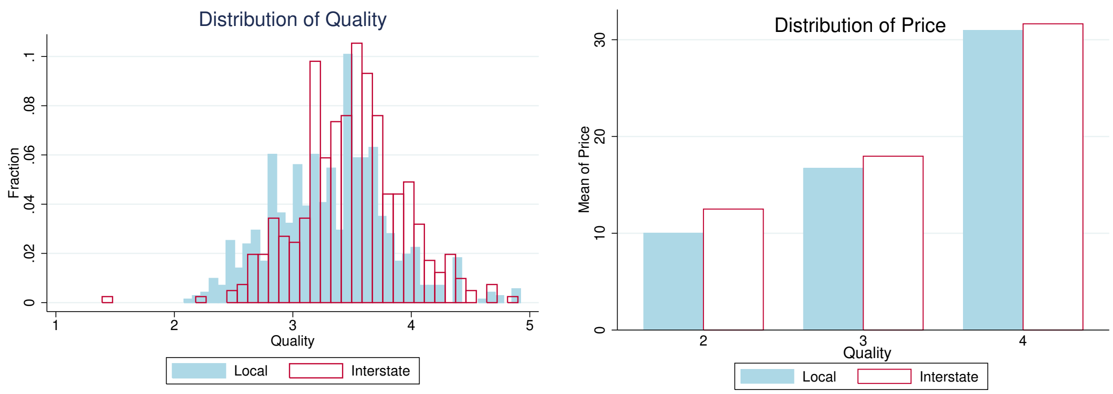
Table A1 shows the change in general quality of trucks from TX transaction data and nationwide auction transaction data. Figure A3 summarizes the price distribution of trucks on different platforms. Figure A4 shows the price distribution of trucks purchased by different types of buyers. Figure A5 presents the variation in the quality and transaction volume across different months and states.

Table A1: Characteristics of Trucks in the TX Transaction Data and Auction Transaction Data

	2016		2018	
	TX, All	Nationwide, Auctions	TX, All	Nationwide, Auctions
age	9.1841	9.1056	9.6960	9.6490
log(mile)	6.0312	5.7716	6.1159	6.0445

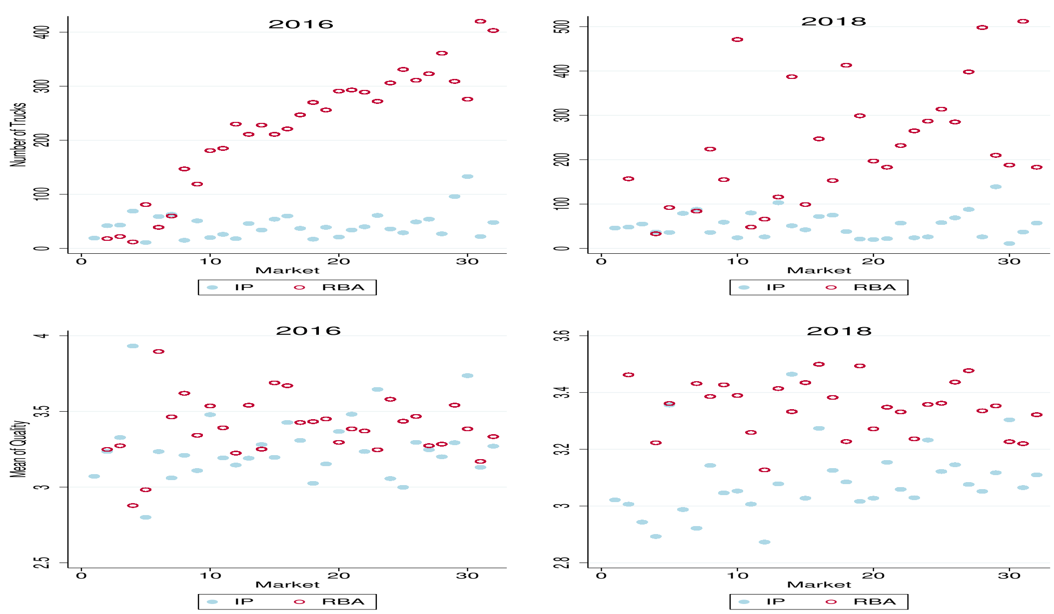
Notes: unit of mileage is 1,000 miles.

Figure A4: The Distribution of Truck Quality and Prices Paid by Different Types of Buyers in Texas



Notes: quality is round to the nearest integers.

Figure A5: Variation in the Number of Trucks Across Markets



Notes: markets are sorted according to the market size pre-merger.

B Supplement to Model

This section is used to supplement the model part. It has two subsections. (1) Markets with at most two different quality levels. First, in a one platform setting, I prove some properties of the equilibrium payoff functions in the auction entry stage. Then, based on these properties, I discuss the economics of more searches, which gives proof for Proposition 1. Based on similar intuition, I discuss the economics of more multihoming buyers in simple settings and prove Proposition 2. (2) I extend the markets to include more complicated structures of available trucks and provide more evidence about the economics of different search choices. It includes a simulation showing the pattern of models with two types of buyers.

B.1 Markets with at Most Two Quality Levels

Assume there are two possible quality levels $q^H > q^L$ in the market. I use $N^{H,A}, N^{H,B}, N^{L,A}, N^{L,B}$ to represent the number of trucks on different platforms with different quality levels, where $N^A = N^{H,A} + N^{L,A}, N^{H,B} + N^{L,B} = N^B, N^A + N^B = N$. Assume buyers can choose to search for one truck or two trucks on one platform or two platforms. The probability of buyers searching for two trucks is Pr^m and the probability of buyers choosing single-homing is ω. Additionally, for simplicity, I assume buyers' WTP for trucks with the same (q,v) is the same on different platforms, i.e., $V^A(q,v) = V^B(q,v) = V(q,v)$. All buyers are ex-ante symmetric. Assume the platform choice of single-homing buyers follows a rule related to the number of trucks on each platform $g(N^A, N^B)$.

B.1.1 One Platform

For now, assume there is only one platform with N goods. The equilibrium payoff function $U^*(q,v)$ is monotonically increasing in v, where $\frac{\partial U^*(q,v)}{\partial v} = \frac{\partial V(q,v)}{\partial v}[1 - Pr^{e^*}(q,v)]^{\gamma N-1} \geq 0$. Intuitively, entry choices of other competitors is independent of buyer $i's$ private value, higher private value can increase buyer $i's$ WTP for the truck and her chance to win the truck. Therefore, higher private value can increase her expected payoffs from an auction for sure. Furthermore, since $V(q,v)$ is convex in v under Assumption 1 and

$$\frac{\partial Pr^{e^*}(q^H,v)}{\partial v} = ...$$
$$-\frac{1-Pr^{m^*}}{N}f(v) - Pr^{m^*}[\frac{\binom{1}{N^H-1}}{\binom{2}{N}}F(v) + \frac{\binom{1}{N^L}}{\binom{2}{N}}F(v'|U^*(q^H,v) = U^*(q^L,v'))]f(v) < 0,$$
$$\frac{\partial Pr^{e^*}(q^L,v)}{\partial v} = ...$$
$$-\frac{1-Pr^{m^*}}{N}f(v) - Pr^{m^*}[\frac{\binom{1}{N^L-1}}{\binom{2}{N}}F(v) + \frac{\binom{1}{N^H}}{\binom{2}{N}}F(v'|U^*(q^L,v) = U^*(q^H,v'))]f(v) < 0,$$

we have $U^*(q,v)$ is convex in v.

Given these properties, I can proof the following Lemma about the equilibrium expected payoff function in the auction entry stage.

Lemma 1. *$\exists v^*$, we have $U^*(q^H,v) \geq U^*(q^L,v)$, $\frac{\partial U^*(q^H,v)}{\partial v} \geq \frac{\partial U^*(q^L,v)}{\partial v}, \forall v \geq v^*$.*

Proof. The proof includes two steps.

In the first step I prove that $\exists v^*$ such that $U^*(q^H,v^*) \geq U^*(q^L,v^*)$ and $\frac{\partial U^*(q^H,v^*)}{\partial v} \geq \frac{\partial U^*(q^L,v^*)}{\partial v}$.

The proof is by contradiction.

- Assume $U^*(q^H,v) < U^*(q^L,v), v \in [\underline{v},\overline{v}]$.

  Under this assumption, a truck with low-quality level will be chosen if a buyer have the same private values for a high-quality truck and a low-quality truck, so $0 \leq Pr^{e^*}(q^H,v) < Pr^{e^*}(q^L,v), 0 > \frac{\partial Pr^{e^*}(q^H,v)}{\partial v} > \frac{\partial Pr^{e^*}(q^L,v)}{\partial v}, \forall v \in [\underline{v},\overline{v}]$.

  Since under Assumption 1,

  $$U^*(q,v) = ...$$
  $$-\int_{\underline{v}}^{v}(\gamma N-1)[V(q,v)-V(q,\tilde{v})][1-Pr^{e^*}(q,\tilde{v})]^{\gamma N-2}\frac{\partial Pr^{e^*}(q,\tilde{v})}{\partial v}d\tilde{v} + ...$$
  $$V(q,\underline{v}) \times [1-Pr^{e^*}(q,\underline{v})]^{\gamma N-1},$$
  $$V(q^H,v) - V(q^H,\tilde{v}) > V(q^L,v) - V(q^L,\tilde{v}), \forall v > \tilde{v},$$

  we have $U^*(q^H,v) > U^*(q^L,v)$, which contradicts the assumption.

- Assume $\exists v', U^*(q^H, v') \geq U^*(q^L, v')$, $\exists v'', U^*(q^H, v'') < U^*(q^L, v'')$ and $\forall v \in [\underline{v}, \overline{v}]$, $0 < \frac{\partial U^*(q^H,v)}{\partial v} < \frac{\partial U^*(q^L,v)}{\partial v}$

  Under this assumption, we have $U^*(q^H, \overline{v}) < U^*(q^L, \overline{v})$. Then, we have $Pr^{e^*}(q^H, \overline{v}) = Pr^{e^*}(q^L, \overline{v}) = 0, 0 > \frac{\partial Pr^{e^*}(q^H,\overline{v})}{\partial v} > \frac{\partial Pr^{e^*}(q^L,\overline{v})}{\partial v}$.

  Since

  $$\frac{\partial U^*(q,v)}{\partial v} = \frac{\partial V(q,v)}{\partial v}[1 - Pr^{e^*}(q,v)]^{\gamma N-1},$$
  $$\frac{\partial V(q^H,v)}{\partial v} > \frac{\partial V(q^L,v)}{\partial v},$$

  we have $\frac{\partial U^*(q^H,\overline{v})}{\partial v} > \frac{\partial U^*(q^L,\overline{v})}{\partial v}$, which contradicts the assumption.

- Assume $\frac{\partial U^*(q^H,v')}{\partial v} < \frac{\partial U^*(q^L,v')}{\partial v}$ whenever $U^*(q^H, v') \geq U^*(q^L, v')$ and $\frac{\partial U^*(q^H,v'')}{\partial v} > \frac{\partial U^*(q^L,v'')}{\partial v}$ for some $U^*(q^H, v'') < U^*(q^L, v'')$.

  If $U^*(q^H, \overline{v}) > U^*(q^L, \overline{v})$, we must have some v satisfies $\frac{\partial U^*(q^H,v)}{\partial v} \geq \frac{\partial U^*(q^L,v)}{\partial v}$ and $U^*(q^H, v) \geq U^*(q^L, v)$; otherwise, we cannot find $U^*(q^H, v) < U^*(q^L, v)$.

  If $U^*(q^H, \overline{v}) < U^*(q^L, \overline{v})$, according to the above, we must have $\frac{\partial U^*(q^H,\overline{v})}{\partial v} \geq \frac{\partial U^*(q^L,\overline{v})}{\partial v}$. The assumption implies $\frac{\partial U^*(q^H,\underline{v})}{\partial v} < \frac{\partial U^*(q^L,\underline{v})}{\partial v}$ and $U^*(q^H, \underline{v}) \geq U^*(q^L, \underline{v})$, which cannot be true when $\frac{\partial V(q,\underline{v})}{\partial v} = V(q, \underline{v})$.

In the second step, I prove $\forall v^*$ such that $U^*(q^H, v^*) \geq U^*(q^L, v^*)$ and $\frac{\partial U^*(q^H,v^*)}{\partial v} \geq \frac{\partial U^*(q^L,v^*)}{\partial v}$, we must have $U^*(q^H, v) \geq U^*(q^L, v)$, $\frac{\partial U^*(q^H,v)}{\partial v} \geq \frac{\partial U^*(q^L,v)}{\partial v}, \forall v \geq v^*$.

If $U^*(q^H, v^*) \geq U^*(q^L, v^*)$, then $\frac{\partial Pr^{e^*}(q^H,v^*)}{\partial v} \leq \frac{\partial Pr^{e^*}(q^L,v^*)}{\partial v} < 0$. Namely,

$$\exists \epsilon \to 0, Pr^{e^*}(q^H, v^* + \epsilon) - Pr^{e^*}(q^L, v^* + \epsilon) \leq Pr^{e^*}(q^H, v^*) - Pr^{e^*}(q^L, v^*).$$

On the other hand,

$$V(q^H, v^* + \epsilon) - V(q^L, v^* + \epsilon) \geq V(q^H, v^*) - V(q^L, v^*).$$

Therefore, we have $\frac{\partial U^*(q^H,v^*+\epsilon)}{\partial v} - \frac{\partial U^*(q^L,v^*+\epsilon)}{\partial v} \geq \frac{\partial U^*(q^H,v^*)}{\partial v} - \frac{\partial U^*(q^L,v^*)}{\partial v} \geq 0$ and $U^*(q^H, v^* + \epsilon) \geq U^*(q^L, v^* + \epsilon)$.

We can iterate this process by using $v^* + \epsilon$ as the starting point. Therefore, we can show that $\forall v \in [v^*, \overline{v}]$, $U^*(q^H, v) \geq U^*(q^L, v)$ and $\frac{\partial U^*(q^H,v)}{\partial v} \geq \frac{\partial U^*(q^L,v)}{\partial v}$. □

Proof of Proposition 1

Proof. Now I will prove how the probability of searching two goods increases from Pr^{m^*} to $Pr^{m^{**}}$ will affect $Pr^{e^*}(q^H,v)$ and $Pr^{e^*}(q^L,v)$. The effect can be analyzed based on the following three equations

$$Pr^{e^*}(q^H,v)-Pr^{e^*}(q^L,v)=Pr^m\{\int_v^{\overline{v}}[\frac{\binom{1}{N^H-1}}{\binom{2}{N}}-\frac{\binom{1}{N^L-1}}{\binom{2}{N}}]F(\tilde{v})f(\tilde{v})d\tilde{v}+...$$
$$\int_v^{\overline{v}}[\frac{\binom{1}{N^L}}{\binom{2}{N}}F(v'|U^*(q^H,\tilde{v})=U^*(q^L,v'))-\frac{\binom{1}{N^H}}{\binom{2}{N}}F(v'|U^*(q^L,\tilde{v})=U^*(q^H,v'))]f(\tilde{v})d\tilde{v}\} \tag{A.1}$$

$$\frac{\partial Pr^{e^*}(q^H,v)}{\partial v}-\frac{\partial Pr^{e^*}(q^L,v)}{\partial v}=-Pr^m\{[\frac{\binom{1}{N^H-1}}{\binom{2}{N}}-\frac{\binom{1}{N^L-1}}{\binom{2}{N}}]F(v)f(v)+...$$
$$[\frac{\binom{1}{N^L}}{\binom{2}{N}}F(v'|U^*(q^H,v)=U^*(q^L,v'))-\frac{\binom{1}{N^H}}{\binom{2}{N}}F(v'|U^*(q^L,v)=U^*(q^H,v'))]f(v)\} \tag{A.2}$$

$$U^*(q^H,v)-U^*(q^L,v)=(\gamma N-1)\{\int_{\underline{v}}^{v}[V(q^L,v)-V(q^L,\tilde{v})][1-Pr^{e^*}(q^L,\tilde{v})]^{\gamma N-2}$$
$$\frac{\partial Pr^{e^*}(q^L,\tilde{v})}{\partial v}-[V(q^H,v)-V(q^H,\tilde{v})][1-Pr^{e^*}(q^H,\tilde{v})]^{\gamma N-2}\frac{\partial Pr^{e^*}(q^H,\tilde{v})}{\partial v}d\tilde{v}\}+...$$
$$V(q^H,\underline{v})[1-Pr^{e^*}(q^H,\underline{v})]^{\gamma N-1}-V(q^L,\underline{v})[1-Pr^{e^*}(q^L,\underline{v})]^{\gamma N-1}. \tag{A.3}$$

From (A.1)(A.2)(A.3), we see that Pr^m affects $Pr^{e^*}(q^H,v)-Pr^{e^*}(q^L,v)$ and $\frac{\partial Pr^{e}*(q^H,v)}{\partial v}-\frac{\partial Pr^{e^*}(q^L,v)}{\partial v}$ through two channels: (1) the direct channel, when Pr^{m^*} increase to $Pr^{m^{**}}$, according to Lemma 1, it can attract more competitive buyers with private value above a threshold to the high-quality auctions while keeping the equilibrium expected payoffs the same. This effect will increase $Pr^{e^*}(q^H,v)-Pr^{e^*}(q^L,v)$ and decrease $\frac{\partial Pr^{e^*}(q^H,v)}{\partial v}-\frac{\partial Pr^{e^*}(q^L,v)}{\partial v}$ when v is above the threshold; (2) the indirect channel, lowering the expected payoffs because of the increased competition from (1). When Pr^m increases, according to (A.3), the difference between $U^*(q^H,v)$ and $U^*(q^L,v)$ becomes smaller.

The value of $\frac{\partial Pr^{e^*}(q^H,v)-Pr^{e^*}(q^L,v)}{\partial Pr^m}$ and $\frac{\partial\frac{\partial Pr^{e^*}(q^H,v)}{\partial v}-\frac{\partial Pr^{e^*}(q^L,v)}{\partial v}}{\partial Pr^m}$ can be calculated using the implicit function theorem and (A.1)(A.2)(A.3). In the new equilibrium, $\exists v^{**}$, for $v\in[v^{**},\overline{v}]$,$\frac{\partial Pr^{e^*}(q^H,v)-Pr^{e^*}(q^L,v)}{\partial Pr^m}\geq 0$. Assume the this is not true. Since $Pr^{e^*}(q^H,\overline{v})=Pr^{e^*}(q^L,\overline{v})=0$, we have $\frac{\partial\frac{\partial Pr^{e^*}(q^H,\overline{v}-\epsilon)}{\partial v}-\frac{\partial Pr^{e^*}(q^L,\overline{v}-\epsilon)}{\partial v}}{\partial Pr^m}>0,\epsilon\to 0$. Therefore, $\frac{\partial U^*(q^H,\overline{v}-\epsilon)-U^*(q^L,\overline{v}-\epsilon)}{\partial Pr^m}>0,\epsilon\to 0$, which contradicts the indirect effect mentioned above. Similarly, we must have $\frac{\partial\frac{\partial Pr^{e^*}(q^H,\overline{v}-\epsilon)}{\partial v}}{\partial Pr^m}<0,\epsilon\to 0$. In sum, $\exists v^{**}$, for $v\in[v^{**},\overline{v}]$, $Pr^{e^*}(q^H,v|Pr^{m^{**}})-Pr^{e^*}(q^L,v|Pr^{m^{**}})\geq Pr^{e^*}(q^H,v|Pr^{m^*})-$

$Pr^{e^*}(q^L, v|Pr^{m^*})$ and $\frac{\partial Pr^{e^*}(q^H,v|Pr^{m^{**}})}{\partial v} < \frac{\partial Pr^{e^*}(q^H,v|Pr^{m^*})}{\partial v}$ when $Pr^{m^{**}} > Pr^{m^*}$.

The probability of the transaction price to be higher than p is equivalent to the second highest WTP among bidders is higher than $p = V(q, v)$.

$$
\begin{aligned}
&Prob(p > \tilde{p}|q, Pr^{m^*}) = Prob(v^{(n-1:n)} > V^{-1}(\tilde{p}, q)|Pr^{m^*}) = ...\\
&1 - [1 - Pr^{e^*}(q, V^{-1}(p, q))]^{\gamma N-1}\\
&Prob(p > \tilde{p}|q^H, Pr^{m^*}) - Prob(p > \tilde{p}|q^L, Pr^{m^*}) = ...\\
&[1 - Pr^{e^*}(q^L, V^{-1}(\tilde{p}, q^L)|Pr^{m^*})]^{\gamma N-1} - [1 - Pr^{e^*}(q^H, V^{-1}(\tilde{p}, q^L)|Pr^{m^*})]^{\gamma N-1} + ...\\
&[1 - Pr^{e^*}(q^H, V^{-1}(\tilde{p}, q^L)|Pr^{m^*})]^{\gamma N-1} - [1 - Pr^{e^*}(q^H, V^{-1}(\tilde{p}, q^H)|Pr^{m^*})]^{\gamma N-1}
\end{aligned}
$$

When $Pr^{e^*}(q^H, V^{-1}(\tilde{p}, q^L)) - Pr^{e^*}(q^L, V^{-1}(\tilde{p}, q^L))$ and $Pr^{e^*}(q^H, V^{-1}(\tilde{p}, q^H))-$ $Pr^{e^*}(q^H, V^{-1}(\tilde{p}, q^L))$ increase, $Prob(p > \tilde{p}|q^H) - Prob(p > \tilde{p}|q^L)$ increases. Namely, we have $Prob(p > \tilde{p}|q^H, Pr^{m^{**}}) - Prob(p > \tilde{p}|q^L, Pr^{m^{**}}) \geq Prob(p > \tilde{p}|q^H, Pr^{m^*}) - Prob(p > \tilde{p}|q^L, Pr^{m^*})$ when $\tilde{p}$ is above a threshold. □

B.1.2 Two Platforms

As mentioned in the main text, the effect of ω^* is smoothing the variation in quality and number of trucks across platforms in different markets. I discuss the effect of lower ω^* (share of single-homing) when there are two types of goods differentiated in their quality.

Proof of Proposition 2

Proof. Under the conditions in Proposition 2 and equation (1)(2) in the auction entry stage, I can get the following two equations:

$$
\begin{aligned}
&U^*(q^A, v, A) = ...\\
&\int_{\underline{v}}^{v} [V(q^A, v) - V(q^L, \tilde{v})] d[1 - Pr^{e^*}(q^A, \tilde{v}, A)]^{\gamma N-1} + V(q^A, \underline{v})[1 - Pr^{e^*}(q^A, \underline{v}, A)]^{\gamma N-1}
\end{aligned}
\tag{A.4}
$$

$$
\begin{aligned}
&Pr^{e^*}(q^A, v, A|q^B = q^H) - Pr^{e^*}(q^A, v, A|q^B = q^L) = (1 - \omega^*)\frac{\binom{1}{N^B}}{\binom{2}{N}} \times ...\\
&\int_{v}^{\overline{v}} F(v'|U^*(q^A, \tilde{v}, A) = U^*(q^H, v', B)) - F(v'|U^*(q^A, \tilde{v}, A) = U^*(q^L, v', B)) f(\tilde{v}) d\tilde{v}.
\end{aligned}
\tag{A.5}
$$

Similar to the one-platform case proved in Lemma 1, there is a threshold of private value, when buyers' private value is above the threshold, we have $U^*(q^H, v', B)) \geq U^*(q^L, v', B))$.

According to (A.5), when buyers conduct multihoming, they are less likely to choose the trucks on Platform A if the trucks on platform B have high quality and their private draws associate with those goods are not low. Similar to the indirect effect mentioned above, when ω decrease and $q^B = q^H$, the competition on platform B is fiercer, resulting in some buyers with moderate private values switch to platform A. Similar to Proposition 1, I can prove that $\exists v^{**}$, for $v \in [v^{**}, \overline{v}], Pr^{e^*}(q^A, v, A|q^B = q^H, \omega^{**}) - Pr^{e^*}(q^A, v, A|q^B = q^L, \omega^{**}) < Pr^{e^*}(q^A, v, A|q^B = q^H, \omega^*) - Pr^{e^*}(q^A, v, A|q^B = q^L, \omega^*)$ and $\frac{\partial Pr^{e^*}(q^A, v, A|q^B = q^H, \omega^*)}{\partial v} < \frac{\partial Pr^{e^*}(q^A, v, A|q^B = q^H, \omega^{**})}{\partial v}$. Then since the final price is second highest WTP among buyers in an auction, we can get $Prob(p^A > \tilde{p}|\overline{q}^B = q^L, \omega^{**}) - Prob(p^A > \tilde{p}|\overline{q}^B = q^H, \omega^{**}) \geq Prob(p^A > \tilde{p}|\overline{q}^B = q^L, \omega^*) - Prob(p^A > \tilde{p}|\overline{q}^B = q^H, \omega^*)$ when $\tilde{p}$ is above a threshold. $\square$

B.2 Markets with More Than Two Quality Levels

For the markets with more complicated structure of available trucks, I do some simulations to present the similar findings about the economics of search choices. Considering the difficulty in proving the two-type model, I also illustrate the findings about two-type model by simulation.

B.2.1 One Type of Buyers

To be specific, I show a simulation result under the specification where the WTP follows log-normal distribution:

$$V(q_j, v_{ij}) = \begin{cases} exp(\theta q_j + v_{ij}) & \text{if } j \text{ is on } A \\ exp(\theta(q_j + \alpha) + v_{ij}) & \text{if } j \text{ is on } B \end{cases}$$

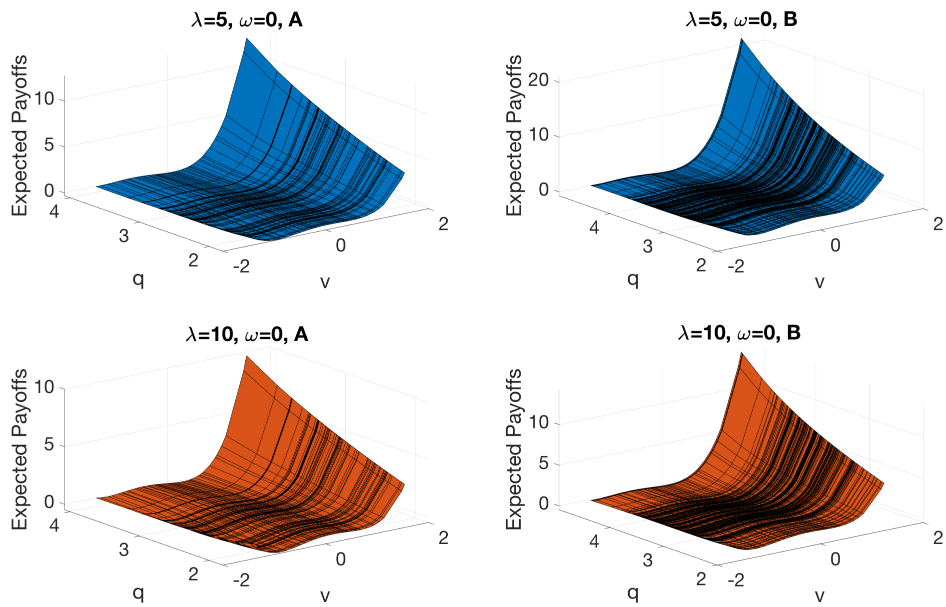
$$\theta = 0.8, v_{ij} \sim N(0, 0.5), \alpha = -0.5.$$

The set of realized trucks available on each platform is the same to the first realized market in the data. I consider two distributions of equilibrium searches:

- Case 1: $m^{\text{multi}} \sim Poisson(5), \omega = 0$;
- Case 2: $m^{\text{multi}} \sim Poisson(10), \omega = 0$.

Figure A6 shows that the expected payoffs from entering an auction U is complementary in (q, v). When all buyers are more likely to search for more trucks in equilibrium,

Figure A6: Expected Payoffs from Entering an Auction $U^*(q, v)$ (One Type of Buyers)



Notes: unit of expected payoffs $\$1,000$.

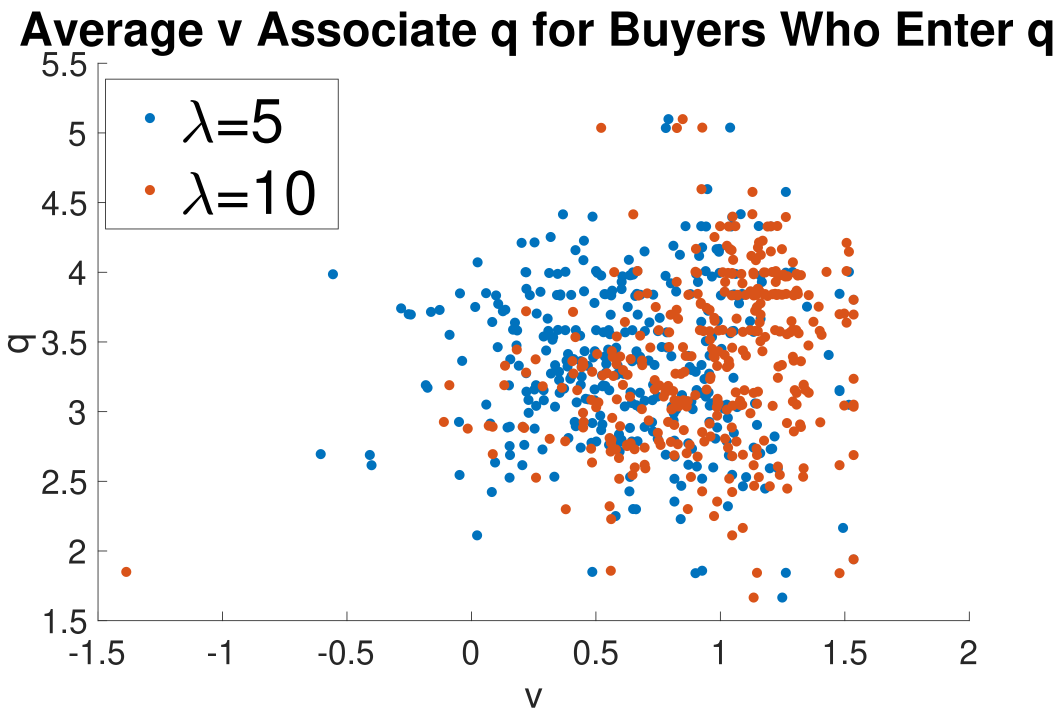
the expected payoffs from entering the popular auctions, i.e., the high-quality auctions on platform B, will decrease significantly.

Figure A7 shows the entry behavior of buyers who search five trucks across platforms on average and buyers who search ten trucks across platforms. I do 100 simulations and calculate the average v when they choose trucks with different q in the two equilibria. We see that under this specification, the buyers who choose to enter auctions with high-quality trucks have higher v on average when all the buyers search for more trucks. Therefore, the trucks with high quality are more likely to be transacted with high price when all buyers search more trucks.

B.2.2 Two Types of Buyers

Buyers with different quality preferences have different expected payoffs from searching, resulting in different equilibrium search choices even if they draw from the same distribution of search costs. Because of the higher WTP for high-quality trucks, the expected gain from more searches among high-type buyers is higher than that among low-type buyers. On the other hand, when both types of buyers search for more trucks, low-type buyers are more likely to lose in auctions with high-quality trucks since there are more high-type

Figure A7: Auction Entry Behavior of Buyers



buyers in those auctions. Notably, some low-type buyers may switch to the auctions with low-quality trucks even if their private value for high-quality truck is high. Given these differences, when the search costs are lower, high-type buyers are more likely to purchase high-quality trucks than low-type buyers. I show this pattern by simulation.

Assume all buyers search on one platform. Here θ can have two different values.

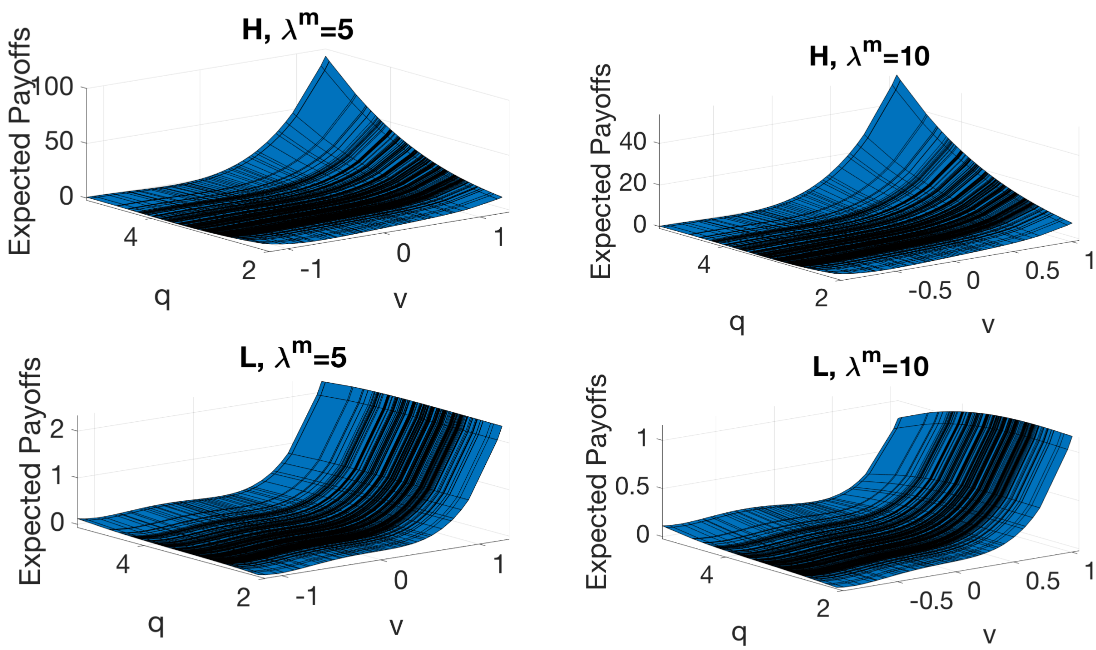
$$V(q_j, v_{ij}) = \; exp(\theta^T q_j + v_{ij}) \; .$$

$$\theta^H = 0.85, \theta^L = 0.6, v_{ij} \sim N(0, 0.5).$$

- Case 1: $m^H \sim Poisson(5), m^L \sim Poisson(5)$;
- Case 2: $m^H \sim Poisson(10), m^L \sim Poisson(10)$.

Figure A8 shows while U^{H*} is still complementary in q and v, it is not true for U^{L*}. Buyers with high quality preference are more likely to choose the auctions with high quality trucks relative to low-type buyers when all of them can search more trucks.

Figure A8: Expected Payoffs from Entering an Auction $U(q, v)$ (Two types of Buyers)



Notes: 1. unit of expected payoffs is $\$1,000$; 2. "H" represents buyers with higher quality preference and "L" represents buyers with low quality preference.

C Supplement to Identification

C.1 Baseline

Proof of Proposition 3

Proof. In the market with $N^H = N, N^L = 0$, according to the expression of $F_{2,\text{price}}$ above, at a specified p, I can solve for the $[(1-Pr^{m^*})F^V(pq^H) + Pr^{m^*}F^V(p|q^H)^2]$ which satisfies the following equation:

$$(1-Pr^{m^*})F^V(p|q^H) + Pr^{m^*}F^V(p|q^H)^2 = 1 - \sqrt{1 - F_{2,\text{price}}(p|q^H, q^H, N^H, N^L)}$$

Similarly to the case where $N^L = N, N^H = 0$.

Therefore, given the $F_{2,\text{price}}(p|q^H, N)$ and $F_{2,\text{price}}(p|q^L, N)$ at a specified p and Pr^{m^*}, I can get corresponding $F^V(p|q^H)$ and $F^V(p|q^L)$ which satisfy following equations:

$$F^V(p|q^H) = \frac{\sqrt{(1-Pr^{m^*})^2 + 4Pr^{m^*}[1 - \sqrt{1 - F_{2,\text{price}}(p|q^H, N)}]} - (1-Pr^{m^*})}{2Pr^{m^*}} \tag{A.6}$$

$$F^V(p|q^L) = \frac{\sqrt{(1-Pr^{m^*})^2 + 4Pr^{m^*}[1 - \sqrt{1 - F_{2,\text{price}}(p|q^L, N)}]} - (1-Pr^{m^*})}{2Pr^{m^*}} \tag{A.7}$$

$$\forall p \in [\underline{V}, \overline{V}]$$

Note that this means that $F_{2,\text{price}}(p|q^H, N) = F_{2,\text{price}}(p|q^H)$. In the market with one quality level and one platform, the price distribution given a truck has two buyers is independent of the number of trucks available in the market as long as $N > 2$.

Finally, using the markets with two different quality levels q^H and q^L in the same market, I can get the condition to pin down Pr^{m^*}:

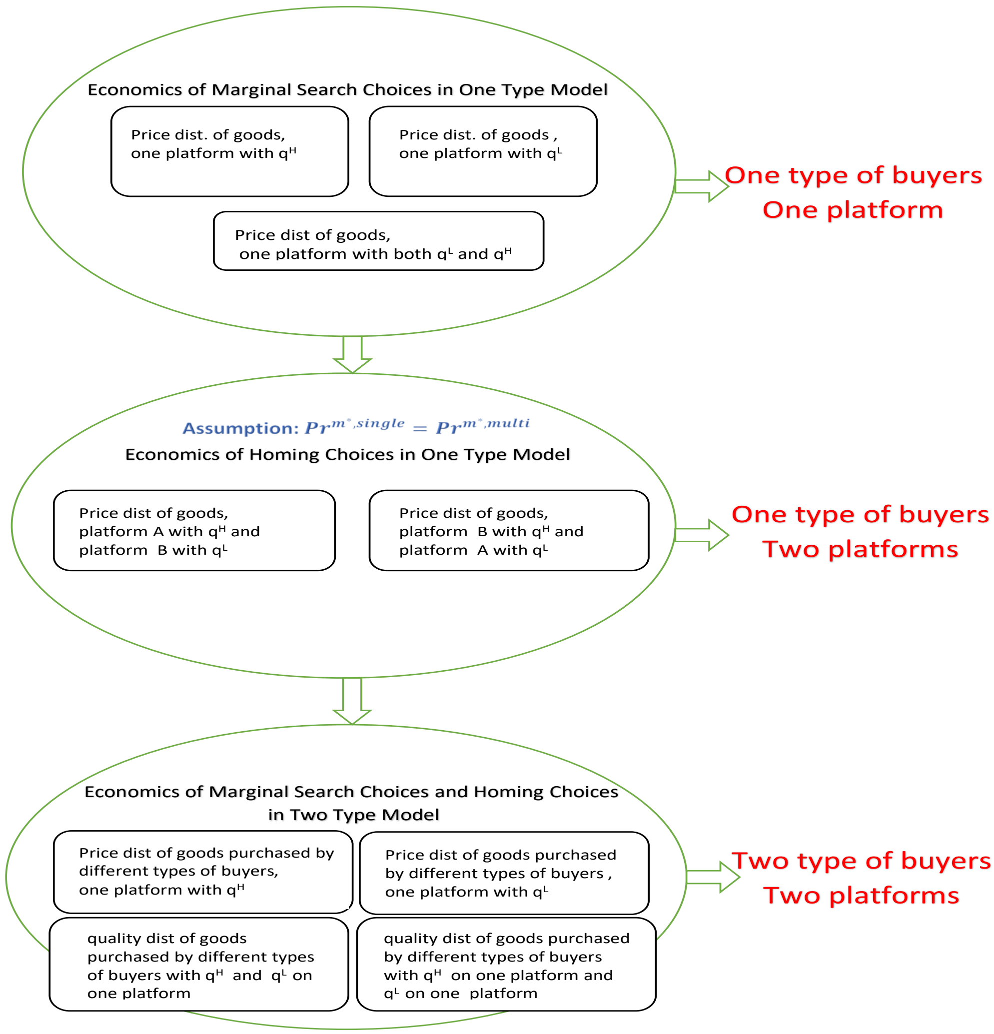
$$
\begin{aligned}
&(1-Pr^{m^*})F^V(p|q^H)+\frac{N^L}{N^H}(1-Pr^{m^*})F^V(p|q^L)+Pr^{m^*}\frac{N^H-1}{N-1}F^V(p|q^H)^2+\ldots\\
&Pr^{m^*}\frac{N^L}{N^H}\frac{N^L-1}{N-1}F^V(p|q^L)^2+\frac{N^L}{N-1}F^V(V^*(p,q^L,q^H)|q^H)F^V(V^*(p,q^H,q^L)|q^L)]=\\
&1-\sqrt{1-F_{2,\text{price}}(p|q^H,q^L,N^H,N^L)}+\frac{N^L}{N^H}[1-\sqrt{1-F_{2,\text{price}}(p|q^L,q^H,N^H,N^L)}]\\
&\text{Where } U^*(p,q^H)=U^*(V^*(p,q^L,q^H),q^L),U^*(p,q^L)=U^*(V^*(p,q^H,q^L),q^H)
\end{aligned}
\tag{A.8}
$$

Note that given the mappings (A.6)(A.7), the equilibrium payoffs U^* can be solved as a function of Pr^{m*} and $F_{2,\text{price}}$. Therefore, by solving equation (A.8), I can get the Pr^{m^*}. Namely, (A.6)(A.7)(A.8) can identify $F^V(\cdot|q^H)$, $F^V(\cdot|q^L)$ and Pr^{m^*}. Note that although the explicit part about Pr^{m^*} in (A.8) just in degree 2, it may enter U^* in higher order. However, equation (A.8) should be satisfied for any $\{q^H,q^L,N^H,N^L\}$ where Pr^{m^*} are the same. Then there is enough conditions to pin down a unique Pr^{m^*}. □

C.2 Extensions

Figure A9 summarizes the data and assumptions used for identify different models mentioned in the text.

Figure A9: Measurements and Assumptions for the Identification of Different Models



D Supplement to Estimation

Algorithm 1 shows the way the details about the algorithm I used to solve for the expected payoff functions in equilibrium, which approximate the payoffs function by two-dimension Lagrange interpolation (Judd [1998]). To speed up the convergence, I update the coefficients for the polynomials "smoothly". This is similar to the way used in Weintraub et al. [2010].

D.1 Algorithm for Solving Equilibrium Payoffs of an Auction

Algorithm 1: Solving for the Equilibrium Expected Payoffs $\mathbf{U}^*(q,v)$

Result: $\mathbf{U}^*(q,v) = \{U^*_T(q,v)\}, T \in \{H,L\}$, platform $\in \{A,B\}$

initialization: $\mathbf{U}^{(0)}(q,v) = \sum_i \sum_j a^{(0)}_{ij} q^i \times v^j, e^*_{-i}(q,v)$

while $\boldsymbol{a}^{(t)} - \boldsymbol{a}^{(t-1)} > tol$ **do**

- $\boldsymbol{a}^{(t)} = \boldsymbol{a}^{(t-2)} + \frac{\boldsymbol{a}^{(t-1)} - \boldsymbol{a}^{(t-2)}}{(t-1)^{\frac{2}{3}}}$
- **for** *Simulation* s **do**
  - *Calculating the realized payoffs from choosing an auction with (q,v) when all the other buyers using* $e^*_{-i}(q,v) : \tilde{U}^{A,s}_T(q,v), \tilde{U}^{B,s}_T(q,v)$.
- **end**
- *Regress* $\tilde{U}^{A,s}_T(q,v|A, Pr^{m,home*}_{-i})$ *and* $\tilde{U}^{B,s}_T(q,v)$ *on* $\sum_i \sum_j q^i \times v^j$ *to get* $\hat{\boldsymbol{a}}$.
- *Update* $\boldsymbol{a}^{(t)} = \hat{\boldsymbol{a}}$ *from the regression*

end

E Supplement to Estimation Results

E.1 Estimation Results for Two-type Model

In the model with two-type of buyers, I estimate models with different settings. For the single-homing buyers, their platform choice rule can follow one rule listed belowI assume the probabilities of a high-type/low-type single-homing buyer to choose online or offline platform keep the same pre- and post-merger. Assume that both types of buyers draw their search costs from the same distribution. Based on this assumption, we can solve for the platform-entry probability of different types of buyers. The estimation results for different settings are shown in Table A2. We can see that the changes in buyers' equilibrium search choices have the similar pattern across different settings: buyers search more trucks and the share of buyers doing single-homing increase significantly (for most cases, more than 20%).

Figure A10 shows the distribution of search costs in the model with two types of buyers under Rule 2 when $share^H = 0.6$ and $share^L = 0.4$. We see that both marginal and fixed search costs decrease significantly. The level of fixed costs is higher in this model since now high-type buyers only search on the offline platform when they are single-homing, the difference between expected payoffs from mulithoming and single-homing is higher.

E.2 Model Fits

Table A3 summarizes how the estimates fit the observation by comparing the target moments. For second set of moments which includes the regression parameters, I compare the two most important pattern: the change in price of high quality trucks ($75th$ percentile of quality) and the change in price sensitivity to the quality of trucks on the other platform.

Table A2: Estimation Results for Two-type Model

	$Share^{H} = 0.62, Share^{L} = 0.38$	$Share^{H} = 0.35, Share^{L} = 0.65$
Quality Pref.		
θ_H	0.7646	0.7538
	(0.0046)	(0.0020)
θ_L	0.7481	0.7303
	(0.0065)	(0.0024)
Dist.of v		
μ	0.0001	0.0001
	(0.0148)	(0.0116)
σ	0.5246	0.5463
	(0.0057)	(0.0072)
Discount of Quality Online		
α	-0.3390	-0.4704
	(0.0059)	(0.0140)
Search Freq.		
λ_H^{Pre}	7.1146	6.6239
	(0.0342)	(0.1334)
λ_H^{Post}	7.6759	7.2809
	(0.0326)	(0.1936)
λ_L^{Pre}	7.2634	6.7231
	(0.0107)	(0.0895)
λ_L^{Post}	7.5115	6.9737
	(0.0069)	(0.1598)
Homing		
$\omega_H^{*,\text{Pre}}$	0.4244	0.5380
	(0.0160)	(0.0326)
$\omega_H^{*,\text{Post}}$	0.3202	0.1016
	(0.0264)	(0.0177)
$\omega_L^{*,\text{Pre}}$	0.3219	0.5272
	(0.0104)	(0.0311))
$\omega_L^{*,\text{Post}}$	0.0999	0.0889
	(0.0069)	(0.0173)
	0.1403	0.1517
	0.4765	0.4552

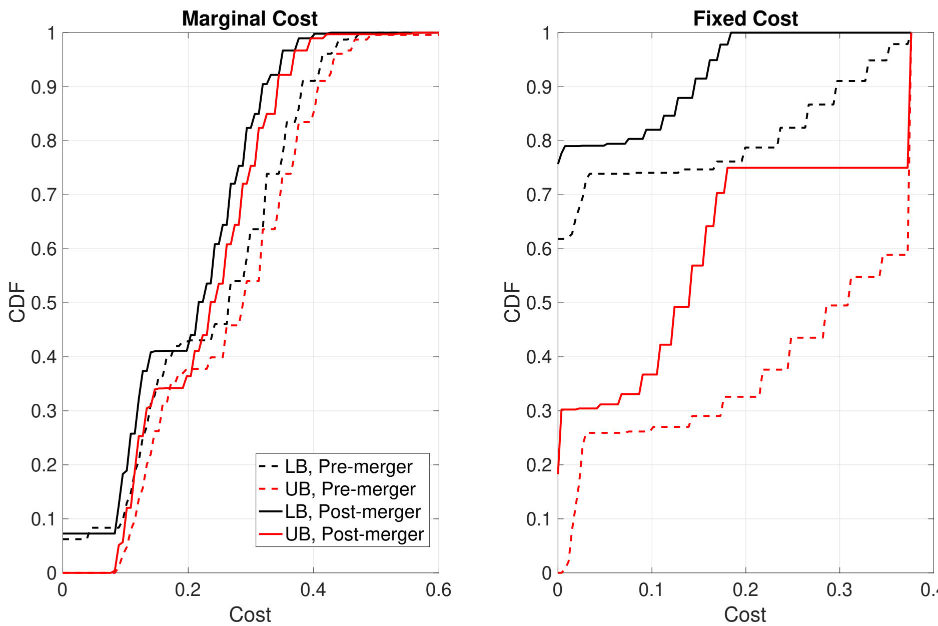
Notes: standard Errors are in parentheses.

Table A3: Model Fitness of Targeted Moments

	One-type		Two-type	
Moment	Observed	Estimated	Observed	Estimated
$\overline{p}^{IP,Pre}$	2.8703	2.7155	2.8703	2.7158
$std(p)^{IP,Pre}(q \geq median)$	0.8997	0.7547	0.8997	0.7534
$\overline{p}^{IP,Pre}(q \geq median)$	3.3525	3.0680	3.3525	3.0954
$\overline{p}^{IP,Pre}(q < median)$	2.4882	2.4362	2.4882	2.4150
$\overline{p}^{RBA,Pre}$	3.0917	3.1277	3.0917	3.1842
$std(p)^{RBA,Pre}$	0.7105	0.7487	0.7105	0.7523
$\overline{p}^{RBA,Pre}(q \geq median)$	3.3811	3.4370	3.3811	3.5248
$\overline{p}^{RBA,Pre}(q < median)$	2.0846	2.3749	2.7457	2.7769
$\overline{p}^{IP,Post}$	2.2634	2.5207	2.2634	2.5176
$std(p)^{IP,Post}$	0.7547	0.7631	0.7547	0.7253
$\overline{p}^{IP,Post}(q \geq median)$	2.8631	3.0401	2.8631	3.0546
$\overline{p}^{IP,Post}(q < median)$	2.0703	2.3534	2.0703	2.3446
$\overline{p}^{RBA,Post}$	3.0731	3.1092	3.0731	3.1488
$std(p)^{RBA,Post}$	0.6409	0.7015	0.6409	0.6984
$\overline{p}^{RBA,Post}(q \geq median)$	3.2613	3.3704	3.2613	3.4356
$\overline{p}^{RBA,Post}(q < median)$	2.8621	2.8162	2.8621	2.8271
$\overline{bid}_1^{IP,Post}$	1.7979	1.8012	1.7979	1.7384
$\frac{\partial p}{\partial q}(q^{75th})^{IP,Post} - ...$ $\frac{\partial p}{\partial q}(q^{75th})^{IP,Pre}$	0.2208	0.0997	0.2208	0.0153
$(\frac{\partial p^{IP,Post}}{\partial \overline{q}^{IP}} - \frac{\partial p^{IP,Pre}}{\partial \overline{q}^{IP}}) - ...$ $(\frac{\partial p^{IP,Post}}{\partial \overline{q}^{RBA}} - \frac{\partial p^{IP,Pre}}{\partial \overline{q}^{RBA}})$	-0.1384	-0.146	-0.1384	-0.1309
$\overline{p}_H^{IP,Pre}$			3.1568	2.8405
$\overline{q}_H^{IP,Pre}$			3.3864	3.4383
$\overline{p}_H^{RBA,Pre}$			3.3077	3.3297
$\overline{q}_H^{RBA,Pre}$			3.6611	3.5094
$\overline{p}_L^{IP,Pre}$			3.0927	3.0851
$\overline{q}_L^{IP,Pre}$			3.3659	3.3779
$\overline{p}_L^{RBA,Pre}$			3.0927	3.085
$\overline{q}_L^{RBA,Pre}$			3.3659	3.3779
$\overline{p}_H^{IP,Post}$			2.8206	2.6720
$\overline{q}_H^{IP,Post}$			3.4887	3.4018
$\overline{p}_H^{RBA,Post}$			3.2399	3.2405
$\overline{q}_H^{RBA,Post}$			3.4887	3.4018
$\overline{p}_L^{IP,Post}$			2.6748	2.5241
$\overline{q}_L^{IP,Post}$			3.1200	3.1512
$\overline{p}_L^{RBA,Post}$			3.0097	3.0410
$\overline{q}_L^{RBA,Post}$			3.3016	3.3174

Notes: unit of price is $\$1,000$.

Figure A10: CDF of Search Costs in Two-type Model



Notes: unit is \$1,000.

F Supplement to Counterfactuals

F.1 Algorithm Used to Solve the New Equilibrium in the Counterfactuals

Algorithm 2 presents the approach I used to solve the new equilibrium search choices used by buyers under alternative settings. Given the estimated search costs, I solve the new probability of each search choice based on the fixed-point theorem. Note since I can only identify the bounds of search cost distribution, I assume that the search costs following uniform distributions whose supports are estimated. The steps used to solve for the new equilibrium are summarized by Algorithm 2. To simplify the problem, in practice, I still assume that a buyer's search frequency follows a Poisson distribution. Therefore, the new equilibrium Pr^{m^*,home^*} is determined by $\{\lambda^{\text{single}*}, \lambda^{\text{multi}*}, \omega^*\}$.

Algorithm 2: Solving for the Equilibrium Search Choices in the Counterfactuals Given H^{mc} and H^{fc}: $Pr^{m^*,\text{home}^*}(H^{mc}, H^{fc})\}$

Result: $Pr^{m^*,\text{home}^*}(H^{mc}, H^{fc})\}$

initialization: ;

while $Pr^{m^{*(t)},home^{*(t)}} - Pr^{m^{*(t-1)},home^{*(t-1)}} > tol$ **do**

- **for** *Simulation s* **do**
  - **for** *Market k* **do**
    - *Calculate the realized payoffs from bidding in the centralized auction with the information from using an search strategy* m_i $\forall i$ *in market k:* $U^{*s}(q, v | Pr_{-i}^{m^{*(t)},home^{*(t)}})$
  - **end**
- **end**
- *1. Calculate the average payoffs from choosing a search choice* $(m_i home_i)$ *by average over all the markets and simulations:* $W_i^{m,home}(Pr_{-i}^{m^{*(t)},home^{*(t)}})$;
- *2. Calculate the range of search costs which can support different search choices according to the equilibrium conditions* $\{\overline{mc}(m,home), \underline{mc}(m,home), \overline{fc}(m,home), \underline{fc}(m,home)\}_{m,home}$;
- *3. Update the equilibrium search choices according to the updated thresholds and* $\{H^{mc}, H^{fc}\}$: $Pr_i^{m^*,home^*}(m, multi) = \int_{\underline{mc}(m,multi)}^{\overline{mc}(m,multi)} \int_{\underline{fc}}^{fc(mc_i)} h^{mc}(mc_i) h^{fc}(fc_i) dmc_i dfc_i$

end