Search and resale frictions in a two-sided online platform: A case of multi-use assets*

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Abstract

How large are two-sided transaction costs in online platform trades, and who are the major beneficiaries of friction cost reductions? Using a dataset of a multi-use train ticket resale market, we analyze the welfare structure with buyer-seller matching frictions on an online platform. Our model shows that competitive online resale market prices work as a conductor of transaction cost externalities, clarifying what types of buyers bear what friction costs. The estimation results show that individual-level welfare losses, which could be considered an online resale market dead-weight loss, are non-negligibly large and heterogeneous across buyers, ranging from 3% to 21% of the new good price. Welfare losses are particularly disadvantageous to users who demand small degrees of usage, as they are more likely to be excluded from trading opportunities. Our model also suggests that, when competitive resale markets experience friction cost reductions, welfare gains are larger among small degree users of resalable goods, providing an explanation for the recent expansion of high-turnover online trades.

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L12
L81

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1 Introduction

Online trades of resalable goods through platforms, such as eBay, Amazon, Yahoo! Auctions, etc., have an increasing presence. In these platforms, large numbers of buyers and sellers are matched up by sacrificing economic costs to find trading partners. Despite the fact that we generally perceive online platform trades as enabling us to buy and sell products with low transaction costs, to the best of our knowledge, the two-sided transaction costs in online platform trades have not been reported. This article contributes to the online platform and resalable goods trading literature by (1) modeling the heterogeneous welfare loss structures among high turnover resalable goods users who demand different degrees of usage; (2) reporting buyer-side search and seller-side resale costs; and (3) reporting the size of individual-level welfare losses.

These days, it is common for consumers to buy a resalable good, use it, and sell it online immediately after usage. This resale-aimed purchase, in which buyers of goods have plans to resell, is a recent trend with increasing popularity. Traditionally, resale market disfunctionalities, such as asymmetric information that creates the market-extinguishing lemon problem, have hindered opportunities for transient consumption of resalable goods. Now, with the emergence of secure, reputable, and convenient websites that mitigate resale market disfunctionalities, online market places such as eBay, Amazon, and Yahoo! Auctions enable us to pursue more and more transient consumption of resalable goods. As a consequence, it is now common to see individual sellers on eBay auctioning off expensive textbooks after an academic semester, mobile phones and high-tech gadgets after a short but specific period of usage (such as until the appearance of a next generation model), video game software a few months after purchase, or and current year models of PRADA shoes and clothes after a few times of wear. However, the online platform literature has a limited understanding of these transient platform trades. Our research fills this gap.

For the sake of empirically deriving welfare implications, we use a unique dataset from an online resalable goods market where perfectly-substitutable goods are traded at high volume. Specifically, the resalable goods are multi-use bundled train tickets which are indivisible yet partially usable and resellable. Notably, as the buyers (train travelers) who purchase these tickets do so purely for the purpose of train riding, market participants treat new and used goods equally based on their demand and degree of usage.

Our empirically analyzed market has the following advantages for a welfare structure investigation. First, the new good seller is a monopolist who sells new resalable goods with a fixed price, while it does not engage in any resale business. Second, the resalable goods are reasonably considered to be perfectly substitutable across any depreciation vintage, especially between new and resold goods. Third, the degree of depreciation is objectively measured and clearly categorized by the recorded usage. Fourth, as the character of the resalable goods is publicly well-known, there is little concern of asymmetric information between sellers and buyers. In fact, the resalable goods could be considered as highly commoditized assets with public price information. Fifth, the online market for the resalable good is sufficiently large, yet it is included in an even larger resale market system. Thus, we can consider the online market as a sub-market, and a price-taking condition is applicable for both purchasing and reselling prices. Sixth, the unique bundling structure of the resalable goods enables us to elucidate the welfare improvements generated through the existence of the resale market, especially when resale transaction costs are low. Seventh, and most importantly, although this product is a specific good, it actually shares many common characteristics of general resalable goods. Therefore, we are able to derive insights on transaction costs and welfare loss (or gain) structures for other commonly-traded resalable good online markets.

Our research is done in two steps: (i) modeling and (ii) estimation. First, for the model analysis, we construct our model based on the observation that a resalable goods user knows her demand, how many degrees of depreciation she wants to consume at least in a stochastic fashion, for modeling the essence of the recent trend of high-turnover online resalable goods trades. Also, we use a competitive price-taking rational expectation equilibrium (Muth 1961) with a no-arbitrage condition in both the primary new good and secondary resale good markets. The price-taking environment is supported as there are numerous buyers and sellers in the resale market. With the nature of perfect substitutability and the simplification of a committed search process in resale markets, the no-arbitrage condition enables us to construct an indifference condition system, from which analytic solutions of competitive resale market prices are derived. In addition, intuitive analytic solutions are obtained for individual-level welfare losses among online resalable good users, which also manifests potential channels of welfare improvements.

Second, for the empirical analysis, following the tradition of the empirical search literature set by the seminal works of Sorensen (2000) and Hong and Shum (2006), we primarily use price data for our main estimation framework. Specifically, we estimate the closed-form solutions of competitive online resale market price equations with observed daily average transaction prices. Furthermore, we apply the sub-market based rational expectation equilibrium framework, in which market participants have expectations on resale prices that agree with empirically observed prices. Then, we use multiple-equation Generalized Method of Moments (GMM) estimations for obtaining the estimates of friction costs and evaluating welfare losses. Identification conditions are also derived.

This research is related to literature investigating online platform markets, resalable good markets, and consumer search. Regarding online platform market research, the seminal paper of Bajari and Hortacsu (2003) shows that there are sizable buyer-side participation costs on eBay auctions. Sailer (2006) proposes a dynamic auction model and estimates the buyer-side search costs on eBay for mobile devices. By using the continuum bidder dynamic programming model, the recent work of Bodoh-Creed et al. (2016) reports that there is a buyer-side opportunity cost on eBay. Oppositely, Dinerstein et al. (2018) construct a seller-side optimization problem and report large seller-side costs on eBay. However, these works leave the joint relation of two-sided transaction costs an open question, to which this study provides an answer.

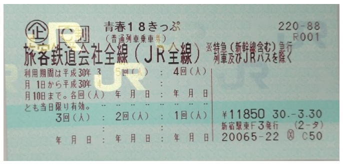
Regarding the resalable goods literature, Chevalier and Goolsbee (2009) study academic textbook markets and support that buyers (college students) are forward-looking and expect resalable goods renewals (new textbook editions). Sweeting (2012) investigates intertemporal pricing behavior of forward-looking sellers with perishable baseball tickets. Most recently, Leslie and Sorensen (2014) construct a model of concert ticket markets with limited supply quantities due to concert venue capacity constraints. The main lesson from this resalable goods literature is simple: resalable goods market outcomes, such as welfare improvements and deterioration, ultimately depend on the magnitude of resale market friction costs. This research extends the above studies by focusing on frequent turn-around in a two-sided large online platform.

Regarding the empirical search literature, Hong and Shum (2006) establish the indifference-condition based structural estimation framework, in which buyer-side search cost distributions are recovered with application to textbook markets. Moraga-González and Wildenbeest (2008) extend the framework of Hong and Shum (2006) to an oligopoly framework for enabling researchers to investigate competition effects in consumer search markets. While both aim to estimate buyer-side search costs and derive welfare analyses, there are two major differences between the above empirical structural search studies and ours. First, while these previous studies construct indifference equations over randomized pricing strategies of price-setting sellers, we construct indifference equations over a no-arbitrage condition across different degrees of depreciation, and buyers and sellers are price takers. Second, the above empirical search studies focus on estimating the distributions of consumer search costs, while our study point-estimates both consumer search and resale costs. This point-estimation specification is used because search and reselling costs are jointly estimated.

Given these preceding studies, our study contributes to the literature in the following four dimensions. First, we model the growing sector of online fast-turnover resalable goods markets. Then, we derive analytic solutions of resale market price distortions and individual-level welfare losses. These solutions provide a clear understanding of welfare structure and welfare loss heterogeneity. Specifically, our model not only sheds light on the welfare improvements generated through the existence of the resale market, but also clarifies the fundamental role of a competitive resale market, splitting resale transaction externalities among market participants based on their intended degree of usage depreciation. Correspondingly, these solutions suggest the channels thorough which welfare improvements propagate when a competitive resale market experiences friction cost reductions. Second, we separately estimate buyer-side search and seller-side resale costs, which are often neglected in online auction market studies. To the best of our knowledge, we are the first to separately report the two-sided costs of an online platform market. In addition, we find that the bidder-side costs are positively correlated with market congestion rates, while the seller-side costs are negatively correlated with market congestion. Third, we empirically assess the magnitude of individual-level welfare losses and their heterogeneity in the multi-use train ticket online market. We find that welfare losses are non-negligibly large and substantially heterogeneous, ranging from 3% to 21% of the new good price. We find the losses are disadvantageous to buyers who intend to consume smaller degrees of usage, as they are more likely to be excluded from trading opportunities. Lastly, we generalize the model with an arbitrary bundle size. Then, we conducts a counterfactual experiment of bundle-size effects from the viewpoint of a regulator, who may design different bundle sizes. This experiment reveals that regulators face challenges to create a Pareto improvement among consumers due to the intrinsic nature of bundled goods markets, i.e. the bundled good demands for dividend remainders.

Before proceeding, as the online platform literature is a vast field, the scope and associated limitations of this study should be mentioned. Our online platform investigation is a competitive sub-market analysis, focusing on two-sided friction costs. Thus, our model takes the entire resale market market level behavior, such as arrivals of sellers and buyers and market clearing, as exogenously given. Nonetheless, the commodity nature and perfect-

Figure 1: *Seishun-18-Kippu* tickets.



(a) Vintage V (New) ticket: Valid for five train rides, sold at the fixed price of $118.50

(b) Vintage IV: Used once

(c) Vintage III: Used twice

(d) Vintage II: Used three times

(e) Vintage I: Used four times

(f) Invalid: Used five times

substitutability of the goods enable us to understand individual-user-level welfare losses happening in the entire market system. Also, we take an agnostic view on the new good seller's pricing behavior by fixing the new good price.[1] In our empirically analyzed dataset, the monopolist in fact kept a fixed new good price throughout the season. Accordingly, empirical investigations of intertemporal price discrimination and industry-wide welfare are beyond the scope of this research, and we focus on user-side welfare losses for transient consumption styles.[2] In addition, we do not estimate bidders' valuations or demand functions. Indeed, with a no-arbitrage condition, our study proposes a convenient method that recovers two-sided costs without estimating demand functions, which is thus flexible to any shape of demand function. Our model recovers two-sided costs that are homogeneous among buyers (and among sellers). However, it does account for the difference between buyer-side and seller-side transaction costs, as well as the heterogeneous welfare losses among users. This limited scope notwithstanding, our model clarifies who bears what costs in a competitive online resale market, indicating welfare improvement potentials.

The rest of this article is organized as follows: Section 2 describes the resalable goods markets from which we obtained our dataset; Section 3 first illustrates a simple model of resalable good users then reports several key observations, including welfare loss structures; Section 4 reports the estimation results; Section 5 explains heterogeneous welfare losses among goods users and discusses the relation between market congestion and friction costs. This section also provides a counterfactual analysis of bundle-size designs with a resale market. Section 6 concludes the article by connecting to recent research. Lastly, the Online Appendix provides a generalized model with an arbitrary number of bundles and stochastic usage, as well as a numerical model of profit and welfare comparisons under different bundle-size and two-part tariff schemes.

2 Market background and data description

This section outlines the resalable goods, bundled train coupon tickets, which are commonly traded in Japan, in four steps. First, we explain that the primary market for these goods is monopolized by a nation-wide semi-privatized railway operator that sets a fixed price for the new good. Second, we illustrate that, due to the commoditized nature of these coupon tickets, the decentralized resale markets are highly synchronized. Third, we provide descriptive statistics with an emphasis on varying market congestion. Lastly, we describe the competitiveness of the resale market.

[1] The Online Appendix provides a model and numerical welfare comparisons, in which profit-maximizing prices are characterized.

[2] Also, our research contributions are orthogonal to the platform reputation and feedback mechanism literature (Melnik and Alm 2002, Houser and Wooders 2006, Bar-Isaac and Tadelis 2008, and Lumeau et al. 2015). Although we acknowledge that reputation causes price dispersion, the effect of reputation is averaged out in this study. However, even in this environment, we still find large price distortions across ticket depreciation vintages (see Figure 2), which warrant further investigation.

2.1 Primary market: Resalable goods sold by a monopolist

We use the online transaction data of coupon tickets, called "*Seishun-18-Kippu*," issued by Japan Railways, known as JR, which is the succeeding and semi–privatized body of the former National Railways in Japan.[3] This coupon ticket enables a holder to have unlimited all-day (within the same day) ride services throughout nation-wide rail-transportation routes operated by JR. A user, however, cannot ride express, overnight sleeper, or bullet trains. The coupon tickets are issued and used each year for limited periods, including the summer break period, and for our study we are empirically analyzing the data extracted from the summer of 2014. The reason for choosing the summer period is that it has the longest resale trading duration and is the most suitable for resalable goods research with resale opportunities.

The valid usage periods are from July 20th to September 10th (i.e. for 53 days), although JR stops selling new tickets after September 1st. After September 11th, JR stops providing any service related to *Seishun-18-Kippu* coupons, and the tickets expire. According to JR, approximately 690,000 coupon tickets were sold throughout the calendar year of 2014, including all spring, summer, and winter breaks, and the amount of new ticket sales was approximately 82 million U.S. dollars ($\approx$ 66 million euros $\approx$ 52 million pounds).[4] During break-season, this coupon ticket can be purchased at every one of the 9,000 JR train stations at the fixed new good price nationwide. Thus, as train travelers must always visit a train station, there is no search cost regarding the purchase of a new ticket.

The characteristics of this coupon ticket are unique, yet the coupon shares many commonalities with other general resalable goods. First, as shown in Figure 1, JR bundles a set of five rides.[5] Throughout this research, we use the term "ride" or "usage" to refer to one unlimited all-day use of the coupon. Thus, a new ticket, which is valid for five rides, means that it is valid for unlimited all-day service five times. JR sells the bundled coupon ticket at $118.50 (or 11,850 Japanese yen $\approx$ € 95 $\approx$ £75), after including the 8% consumption tax.[6] This new coupon ticket price is fixed nationwide and throughout the break season. Importantly, JR neither allows nor sells any other denominations of this coupon. Thus, there is no unbundled *Seishun-18-Kippu* coupon traded in either primary or resale markets.

A *Seishun-18-Kippu* ticket can be partially used, however. Therefore, similar to many other general resalable goods, the good is indivisible yet partially usable. The photos of such partially used coupon tickets are listed in Figure 1 (b) to (e). We categorize such partially used tickets as Vintage IV, III, II, and I, according to their remaining usages. For instance, the Vintage III ticket is still valid for three rides. In addition we refer to the new ticket (listed in Figure 1 (a)) as a new or Vintage V ticket, as it is valid for five rides with the fixed new good price. Lastly, one of the convenient characteristics is that a ticket can be used by a single person or group members who take a train together, allowing large travel plan flexibility among users. Note that as JR is the only seller of the new tickets, it is considered to be a monopoly seller of new tickets. In addition, JR does not engage in any means of resale business.

The primary and secondary markets of *Seishun-18-Kippu* are considered to be separated from other travel service markets in Japan for the following reasons. First, due to its time-consuming nature, *Seishun-18-Kippu* is different from other types of train services (i.e. rapid express, overnight sleeper, and bullet trains) offered by JR. In fact, the coupon is well-known among young people as an extremely cheap yet extremely time-consuming means of transportation during break seasons. Second, all other private railways in Japan are localized and regionally operated. Thus, given the nature of nationwide usability, the coupon is reasonably considered to have negligibly low substitutability with other train tickets offered by other private railways, as buyers of the *Seishun-18-Kippu* tickets are different from buyers of tickets issued by regional railways. Lastly, bus travel is faster than train travel with the *Seishun-18-Kippu* ticket. However, a bus trip is relatively more expensive in Japan.[7]

[3] The direct translation of "*Seishun*" is "youth" and "*Kippu*" is "ticket," yet the literal meaning here refers to a ticket for college-aged (approximately age *18*) students. As the name indicates, JR targets selling these coupon tickets to students who have ample time during their school breaks to afford slow and frequently-stopping train schedules. There is, however, no age restriction on purchasing this ticket and a student card is not required. Thus, anyone can purchase this coupon ticket. See `http://www.jreast.co.jp/e/pass/seishun18.html` (in English, accessed 2019, April 3rd) for the details of this coupon.

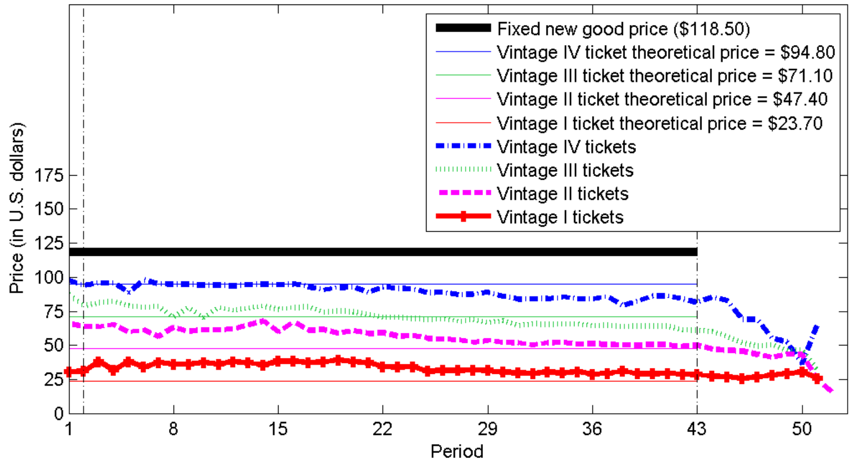
[4] Source: *Kanagawa Shinbun* newspaper, 2015 March 15th, Morning Edition.

[5] These photos are taken by the author in March 2018.

[6] Throughout this research, we use the U.S. dollar notation with a fixed exchange rate of 1 U.S. dollar = 100 Japanese yen ($\approx$ € 0.801 $\approx$ £0.633) for the simplicity of discussion. There is no official announcement regarding reasons behind the fixed new ticket price of $118.50 or the five-ride bundling.

[7] The Online Appendix provides a model with an inter-city bus alternative, which is considered to be the closest substitute of *Seishun-18-Kippu* tickets in terms of transportation time and monetary cost. We re-estimate our model with the bus option and obtain a nearly

Figure 2: Observed and theoretical prices.



2.2 Secondary markets

Due to their partial-usability and flexible usage nature, the used *Seishun-18-Kippu* coupon tickets are widely traded in secondary markets in Japan, such as on a large-size online auction site and in second-hand ticket scalping shops. Among them, Yahoo! Auctions is the most well-known online trading place, and it is data from here that we focus on.[8] In fact, the number of partially-used *Seishun-18-Kippu* coupon tickets traded on the Yahoo! Auctions site per day exceeds an average of one hundred during the summer break season, as will be explained later in Table 1. Specifically, during our analyzed periods, approximately 6,000 coupon tickets were transacted on Yahoo! Auctions' redistribution platform.

Regarding resale market prices, averaged daily transacted prices for each vintage category in the summer of 2014 are plotted in Figure 2 from periods 1 (July 20th) to 53 (September 10th). The solid and perfectly horizontal line is added for depicting the fixed new price set by JR, $\overline{P}^{\mathrm{V,New}} = \$118.50$. We also add the dashed vertical lines at $t = 1$ and 43 for indicating the start and end of the data analyzing periods for our estimations. In Figure 2, we observe that the within-a-day-average transacted prices of Vintage IV, III, II, and I tickets are slightly and gradually decreasing over the sampled period. We also observe that, after period 43 (August 31st), when JR stops selling new tickets, the average daily transaction prices move greatly, before dropping off at the expiring date of period 53 (September 10th).[9]

For the sake of simplified discussions, in Figure 2, we also add the horizontal lines of 80%, 60%, 40%, and 20% of the new goods prices, called theoretical prices, that have theoretical foundations to be explained in the modeling section. Specifically, theoretical prices are $P^{\mathrm{IV,Theo}} = \$94.80$ (= €76 = £60), $P^{\mathrm{III,Theo}} = \$71.10$ (= €57 = £45), $P^{\mathrm{II,Theo}} = \$47.40$ (= €38 = £30), and $P^{\mathrm{I,Theo}} = \$23.70$ (= €19 = £15). Interestingly, we discover that observed average transaction prices for Vintage II and I tickets are mostly above the theoretical prices.

Next, Figures 3 and 4 describe the number of transacted supplies and total number of bidders at each pe-

identical estimation result.

[8]After its initial success in the U.S., Yahoo! Auctions was launched in Japan in 1998, and offers nearly identical online auction services to eBay. Many studies use data from Yahoo! Auctions, e.g. Houser and Wooders (2005) [U.S. data], Glover and Raviv (2012) [U.S. data], and Tsuchihashi (2012) [Japanese data]. Note that eBay, the dominant online auction platform in North America, was launched in Japan in 1999, but exited from Japan in 2002 due to the low number of users. As a consequence, Yahoo! Auctions is a near monopoly online-auction platform in Japan, and its share of online trades was 76 percent as of June 2014. The second largest in Japan, Rakuten Auction, exited the market in Oct. 2016 for the same reason as eBay. Due to this dominant position of Yahoo! Auctions in Japan, we do not model competition among online platforms. Also, we take an agnostic view on platform transaction charges. This is because charges are determined at the entire platform level, and our analyzed market is only a small part of Yahoo! Auctions as a whole. See Rochet and Tirole (2003), Armstrong (2006), Jeitschko and Tremblay (2014), and Jin and Rysman (2015) for competition among two-sided platforms, and Baye and Morgan (2001) and Deltas and Jeitschko (2007) for monopoly platform charges with two-sided endogenous entries.

[9]The exception is Vintage IV ticket prices that skyrocket at the end of the break season. However, this ascended price is based on the result of only one transaction at period 51 (September 8th) and could be considered as an outlier. There were no recorded transactions at period 53 (September 10th) for any vintage.

Figure 3: Observed number of transacted supply.

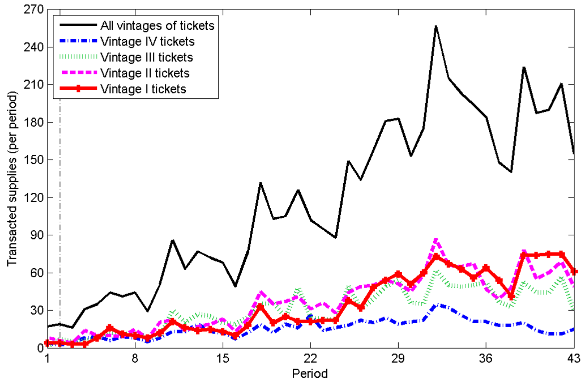
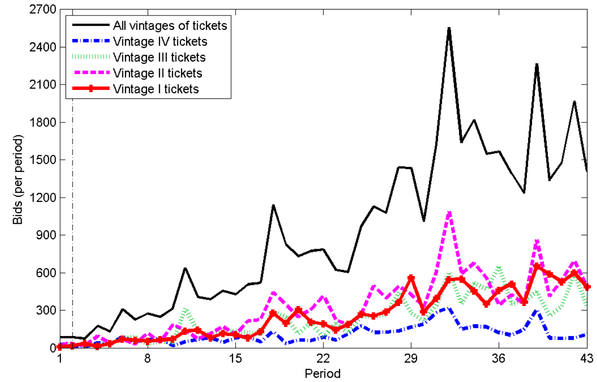


Figure 4: Observed number of total within-an-auction distinct bids.



riod. The number of transacted supplies (TS_t) is the number of auctions at which sellers and bidders successfully matched and completed transactions during period t. In addition, the number of bids (B_ts) is a summation of submitted bids by within-auction distinct bidders, illustrated in Figure 4.[10] Both figures depict that the market size and thickness change widely: thin at the beginning and gradually increasing and developing throughout. We will have a discussion on the market friction costs and congestion in the empirical section.

2.3 Descriptive statistics

For the sake of simplifying the empirical investigation, we primarily aggregate data within a period (or, equivalently, within a day) throughout this study. Regarding the time framework, we use a time period index of $t \in \{1, 2, 3, 4, \cdots, T = 43, \cdots, \overline{T} = 53\}$. Specifically, for our structural estimation, we use data for periods $t = 2 \sim 43$ (July 21st $\sim$ August 31st, 42 days) to investigate the market friction costs, welfare implications, and market congestion (i.e. market thickness). Within the investigation periods, we further divide them into six terms: Term ① for $t = 2 \sim 8$; Term ② for $t = 9 \sim 15$; Term ③ for $t = 16 \sim 22$; Term ④ for $t = 23 \sim 29$; Term ⑤ for $t = 30 \sim 36$, and Term ⑥ for $t = 37 \sim 43$. Term-by-term averaged descriptive statistics are reported in Table 1.[11]

Table 1 lists the descriptive statistics of within-a-term average resale market transaction prices, denoted by P_t^k for $k \in \{\text{I}, \text{II}, \text{III}, \text{IV}\}$. Specifically, as seen in Figure 2 and Table 1, one of the notable features is that resale market prices are not proportional to the remaining usage. In other words, resale market prices are skewed in terms of remaining usage. For instance, the average transaction price for Vintage III tickets ($71.23) is far less than three times that of Vintage I tickets ($33.52), indicating potential price distortions caused by resale market frictions.

The number of transacted supplies (TS_t^k where $k \in \{\text{I}, \text{II}, \text{III}, \text{IV}\}$) broadly measures substitutable products for a bidder at period t within a vintage. In addition, we calculate $TS_t^{\text{All}} \equiv TS_t^{\text{I}} + TS_t^{\text{II}} + TS_t^{\text{III}} + TS_t^{\text{IV}}$ as a crude measure of total substitutable options. Specifically, Table 1 shows that a bidder has, on average, $TS_t^{\text{All}} = 118.88$ alternatives within a period. This number could be interpreted to mean that a buyer, on average, has quite a large number of alternative and substitutable tickets in this online resale market system.

Next, we calculate $B_t^{\text{All}} \equiv B_t^{\text{I}} + B_t^{\text{II}} + B_t^{\text{III}} + B_t^{\text{IV}}$ as an indicator of the total number of within-an-auction-distinct bidders who were involved with *Seishun-18-Kippu* resale transactions during a period t. The mean of B_t^{All} is 941.98, which could be viewed as a large number, and so we can consider that this market attracts quite a large number of bids, on average.

Subsequently, we calculate bidder-to-transacted-supply ratios, $R_t^k \equiv B_t^k / TS_t^k$ for $k \in \{\text{I}, \text{II}, \text{III}, \text{IV}\}$ for understanding the bidder-side opportunity cost. Note that if this measurement is large, a bidder has to sacrifice a large opportunity cost for searching, bidding, and obtaining a ticket in this resale market system. This is because there is, on average, a higher number of competing bidders and, thus, a bidder may waste her time by submitting unsuccessful (i.e. non-winning) bids. R_t^ks are depicted in Table 1 and plotted in Figure 5, reporting that a bidder

[10] As a caveat, Yahoo! Auctions lists user IDs in a masked format, such as "i*s*a***" or "n*k*t***." Thus, B_t is not a number of distinctive bidders.

[11] In Table 1, we first calculate daily (within-period) average values. We then calculate the average of daily values within each term. Descriptive statistics for the entire period are also reported in the Online Appendix.

Table 1: Descriptive statistics by term.

Variable	Term ① $t = 2 \sim 8$ Mean	Term ② $t = 9 \sim 15$ Mean	Term ③ $t = 16 \sim 22$ Mean	Term ④ $t = 23 \sim 29$ Mean	Term ⑤ $t = 30 \sim 36$ Mean	Term ⑥ $t = 37 \sim 43$ Mean	Term ①~⑥ $t = 2 \sim 43$ Mean
Prices:							
P_t^{IV}	\$94.57	\$94.43	\$92.19	\$89.23	\$84.62	\$83.59	\$89.77
P_t^{III}	\$78.36	\$76.27	\$74.73	\$68.90	\$65.76	\$63.35	\$71.23
P_t^{II}	\$61.88	\$62.54	\$61.03	\$54.77	\$51.48	\$50.30	\$57.00
P_t^{I}	\$35.26	\$36.96	\$37.48	\$32.24	\$29.85	\$29.30	\$33.52
Transacted supplies:							
TS_t^{IV}	6.57	11.86	15.86	19.00	25.43	15.29	15.67
TS_t^{III}	8.71	20.14	30.00	38.14	47.71	42.29	31.17
TS_t^{II}	9.71	17.57	32.14	44.57	62.14	56.86	37.17
TS_t^{I}	7.86	14.14	21.14	39.29	62.00	64.86	34.88
TS_t^{All}	32.86	63.71	99.14	141.00	197.29	179.29	118.88
Bidders:							
B_t^{IV}	41.29	59.86	74.43	129.57	201.29	128.57	105.83
B_t^{III}	43.00	129.29	167.14	259.00	447.86	384.43	238.45
B_t^{II}	57.00	119.57	314.71	354.86	597.57	538.57	330.38
B_t^{I}	41.14	102.00	198.29	295.71	434.43	532.29	267.31
B_t^{All}	182.43	410.71	754.57	1039.14	1681.14	1583.86	941.98
Bidder-seller ratios:							
R_t^{IV}	5.98	5.90	5.36	6.83	8.05	8.04	6.69
R_t^{III}	4.64	6.11	5.53	6.90	9.24	9.22	6.94
R_t^{II}	5.51	6.78	10.55	7.76	9.30	9.39	8.21
R_t^{I}	5.68	7.27	9.23	7.49	6.93	8.29	7.48
R_t^{All}	5.34	6.60	7.79	7.29	8.42	8.81	7.37
Number of periods	7	7	7	7	7	7	42

The numbers above are averaged within a term (7 periods).
P_t^k is the averaged daily transacted price of Vintage $k \in \{\mathrm{I,II,III,IV}\}$ tickets at period t.
TS_t^k is the total number of transacted supplies of Vintage k tickets within period t.
B_t^k is the total number of bids submitted by within-an-auction-distinct bidders for Vintage k tickets.
R_t^k is the number of bids to number of sellers ratio (B_t^k/S_t^k) for Vintage k ticket transactions.
$TS_t^{\mathrm{All}} \equiv TS_t^{\mathrm{IV}} + TS_t^{\mathrm{III}} + TS_t^{\mathrm{II}} + TS_t^{\mathrm{I}}$, $B_t^{\mathrm{All}} \equiv B_t^{\mathrm{IV}} + B_t^{\mathrm{III}} + B_t^{\mathrm{II}} + B_t^{\mathrm{I}}$, and $R_t^{\mathrm{All}} \equiv B_t^{\mathrm{All}}/S_t^{\mathrm{All}}$.

Figure 5: Bidder-seller ratio.

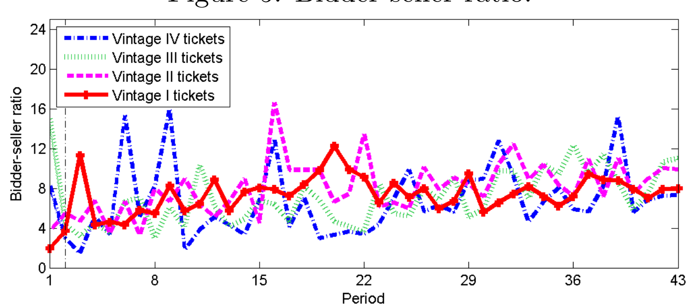
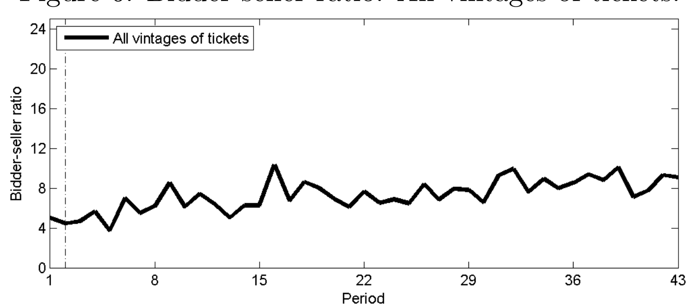


Figure 6: Bidder-seller ratio: All vintages of tickets.



competes with 6.37 (= 7.37 − 1) competitors at an auction, on average. Interestingly, although the numbers of transacted supplies differ widely across vintages as represented in Figure 3, R_t^ks do not vary across vintages (except initial periods) in Figure 5, and all four vintages tend to have similar ratios. This observation can be interpreted to indicate that bidders substitute across vintages with different degrees of remaining usages, as coupon tickets are commoditized and resellable later. Such substitutability leads to assimilations of R_t^ks. This substitutability is explored in the modeling section.

Lastly, we compute the bidder-to-transacted-supply ratio for all vintages, $R_t^{\text{All}} \equiv B_t^{\text{All}}/TS_t^{\text{All}}$, as a measurement of the bidder-side market congestion. The ratio is plotted in Figure 6, and we observe that it is gradually increasing over time. This observation means that a bidder, on average, has to compete with more bidders and the likelihood of obtaining an auctioned ticket through the currently bid-on auction is decreasing over time. From the perspective of the bidders, the searching process in these resale auction markets could gradually become more costly as the likelihood of being matched with a seller at an auction decreases.

2.4 Competitive entire resale market and online sub-market

In this subsection, based on the descriptive statistics above, we illustrate the resale market structures of *Seishun-18-Kippu* tickets. Hereafter, we use the phrase *the entire resale market* to describe the market system that includes both over-the-counter and online resale markets. First, we explain the resale market synchronicity due to the commodity, public information, and perfect substitutability natures of the tickets. Second, we illustrate the nesting structure of the entire resale market and online sub-market of Yahoo! Auctions that is considered to have a price-taking environment. Lastly, we describe the exploitation of product characteristics and the resale market structure.

First, the resale markets for *Seishun-18-Kippu* tickets are highly synchronized. Thanks to their flexible usage, the coupon tickets are highly commoditized with publicly-known characteristics and little asymmetric information. In addition to the Yahoo! Auctions online resale market, there are 774 over-the-counter ticket scalping shops in Japan nationwide as of 2014, and *Seishun-18-Kippu* coupon tickets are one of their most frequently traded tickets.[12] Notably, several ticket scalping shop chains have high trading volumes and post *Seishun-18-Kippu* daily buying and selling prices on their websites throughout the season. Regarding online resale trades, there is a free website in Japan that posts daily average online transaction prices for current and past periods.[13] Moreover, there exist online forums disseminating price information. The public price information nature of the markets and the unique characteristics of the resalable goods lead to *Seishun-18-Kippu* tickets being treated as commodity assets, and the entire resale market prices are considered to be synchronized.

Second, given the large number of Yahoo! Auctions market participants listed in Table 1 and the entire resale market synchronizations described above, the Yahoo! Auctions resale market system can be considered to have a competitive and price-taking environment (see Esteban and Shum 2007, Chen et al. 2013, and Gavazza et al. 2014). This is because *Seishun-18-Kippu* tickets traded in the Yahoo! Auctions platform make up a small portion of the entire market, and the online platform is considered to be a small sub-market of the entire resale market system. Accordingly, entire resale market level resale prices are determined by the market clearing conditions of the entire resale market system, and Yahoo! Auctions market participants take them as exogenously given. One may consider our study as a partial and price-taking sub-market study in which prices are governed by the competitive equilibrium framework of the entire resale market system. The Online Appendix has detailed discussions on the sub-market structure and price-taking environment.

Third, given these environments, we contribute to the literature by overcoming a common limitation in resale market studies, that of resale transaction data availability. Despite the fact that our online data extracted from Yahoo! Auctions does not include complete resale transactions, the recorded prices in our dataset are generated from a well-synchronized system of the entire resale market. Therefore, the observed prices in our dataset intrinsically contain the price information of the over-the-counter ticket scalping shop resale market. Given these observations, the price-taking and sub-market environment is suitable for structural research with friction costs, illustrated in the next section.

3 A model of resale goods markets and welfare implications

In this section, we first describe an empirical model of resale markets with perfectly substitutable resalable goods. Then, we illustrate the key settings and their economic interpretations, including analytic resale price equations and individual-level welfare implications. Lastly, we explain the connection between individual- and market-level

[12] Data source: `http://o-dekake.net/kinken/`, `http://www.kinken-shop.com/`, and `https://kinkenshop.sakura.ne.jp/index.html` (in Japanese, last accessed 2019, April 3rd).

[13] See `en.aucfan.com` (in Japanese, accessed 2019, April 3rd) for such daily online trade prices.

welfares. The primary goal here is to construct a minimalistic model that enables us to estimate and interpret online resale market friction costs.

3.1 A model of competitive resale goods markets

A monopolist of new goods (i.e. JR) supplies new resalable goods in a primary market without the restriction of a supply capacity, at least within a relevant range of supply. The good is indivisible yet partially usable, and the degree of depreciation is measured by the remaining usage, denoted as V, VI, III, II, and I. For an exogenous reason, the monopolist offers a new good with the degree of depreciation V and is committed to the new goods price $\overline{P}^{\mathrm{V,New}}$.[14] Also, the monopolist does not engage in any resale trade. However, used goods can be traded in a competitive resale market.

For obtaining analytic resale prices and welfare solutions, we use the following settings. Each of these assumptions and economic interpretations will be explained in detail when they appear in this section. They are: a buyer knows her resalable good consumption plan at least in a stochastic usage fashion; exogenous seller arrival processes; two-period-like model with rational expectations; no separate purchase; committed resale market search; and a competitive price-taking resale market with no arbitrage opportunity.

By reflecting the recently observed rapid-turnover trades with resale-aimed purchases, we construct a model in which a buyer knows the plan for her resalable goods usage in advance (i.e. how many train rides she will use at least in a stochastic usage manner).[15] Such planned usage is legitimate in our investigation as, upon a purchase, a traveler has to coordinate several other travel-related issues, such as hotel bookings, travel itinerary, meeting times with friends, sightseeing bookings, etc. Accordingly, we use the following notations: e for a buyer who demands five train rides; d for a buyer who has a demand for four; c for a buyer for three; b for two; and a for one.

We have an exogenous arrival process of sellers that is common knowledge among market participants.[16] We use the notation of V for describing a private-value-based willingness-to-pay upon a purchase of a new or used good. In addition, we use the generic index of i for denoting a heterogeneous buyer. We describe buyers as "heterogeneous" since they have different levels of willingness-to-pay at different times. For example, at period t, a buyer i who demands four rides (i.e. a type d buyer) with a specific travel schedule arrives to the resale market with her willingness-to-pay $V_{t,d,i}$ for the service of four train rides. As she has an upcoming travel plan and must go on the trip, we simplify her willingness-to-pay for a *Seishun-18-Kippu* train ticket to be zero after period t. Also, as seen in Figure 2, the resale market prices are gradually decreasing over time. Accordingly, a buyer does not have a monetary incentive to purchase a used ticket earlier than period t. For these transitory valuation reasons, we mostly omit the time script, denoting the valuation as $V_{d,i}$.

We define the following three types of resale market friction costs. The first friction cost is *search-and-bidding cost* ($Search_t$) for capturing the buyer-side opportunity cost for the searching process. Such a cost includes: looking up a desired good in an online resale market; investigating the details (e.g. shipping method after winning and shipping timing); paying attention to relevant auctions; making a proxy bid; awaiting the result; and potentially re-participating in other auctions if she fails to obtain a currently bid-on good. We allow for this search-and-bidding cost to vary across periods. This is because, as manifested in the descriptive statistics section, market congestion changes greatly, and search-and-bidding costs are considered to be related to the market congestion. In addition, we normalize the search cost of buying a new good at zero. This normalization is justified since a ticket buyer (a train traveler) must always go to a train station when she travels, and a new ticket is sold only at JR train stations. The second type of resale market friction cost is an *expected resale transaction cost* ($Resale_t$) that captures the secondary market seller-side opportunity cost for an online resale transaction. Such opportunity costs include: preparing photos and written explanations on an auction website; answering inquiries from potential buyers; awaiting the auction outcome; shipping the auctioned good to the winner; and potentially having to resubmit a good in the case of an unsuccessful sale. Similar to the search-and-bidding cost described above, we add the time index to the search cost for capturing the differing degrees of market congestion. The third friction cost is a *scrap cost* ($Scrap$) that captures a disposal cost that a user incurs when she uses up a resalable good. We include this scrap cost for broadening economic interpretations and the generalizability of our model.

[14] The Online Appendix provides a model for an optimal monopoly price.

[15] See Holmes (2011) for a dynamic modeling with perfect foresight.

[16] See also Sailer (2006), Hendricks and Sorensen (2015), Backus and Lewis (2016), and Bodoh-Creed et al. (2016), which model similar settings of exogenous supply, for further discussions.

Given this setup, we use a two-period-like model in which a forward-looking and resale-motivated resalable good buyer (e.g. Chevalier and Goolsbee 2009) considers an expected resale price. Specifically, we use the notation of $\mathbb{EP}_t^k$ for the expected resale price of a vintage k ticket at period t, wheere $k \in \{\text{I, II, III, IV}\}$, and three different empirical constructions of $\mathbb{EP}_t^k$ are examined in the estimation section later. Then, we consider heterogeneous types of users. Throughout this section, we consider four types of users, type-d, -c, -b, and -a: A type-d user demands four rides, a type-c user demands three, and so on.[17]

A heterogeneous type-d buyer (who has a demand of four train rides) with a buyer index i has the following two purchasing options:

$$
\begin{aligned}
U_{d,i}^{\text{V,New}} &= V_{d,i} - \overline{P}^{\text{V,New}} + \mathbb{EP}_t^{\text{I}} - \mathit{Resale}_t && (d\text{-V})\\
U_{d,i}^{\text{IV}} &= V_{d,i} - P_t^{\text{IV}} - \mathit{Search}_t - \mathit{Scrap}. && (d\text{-IV})
\end{aligned}
$$

One could view the above utility specifications as a two-period model with no time discounting in which a buyer purchases a (new or used) good today and potentially resells the remaining usage later. No time discounting is innocuous as our empirically analyzed resale transactions happened within a short summer break season. Equation (d-V) describes the utility gain from purchasing a new ticket from a primary market (i.e. from JR) for a buyer who will later resell the remaining one train ride in the online resale market with the sacrifice of the resale transaction cost. On the other hand, Equation (d-IV) illustrates the gains from purchasing a slightly used Vintage IV ticket in the secondary market with the sacrifice of a search-and-bidding cost and a scrap cost upon using it up. In both Equations (d-V) and (d-IV), as the new and used goods are perfectly substitutable, the buyer has the same utility $V_{d,i}$. In addition, our simplified model excludes separate purchases. This means that a type d buyer i who demands four usages does not pursue the separate purchases of (i) a Vintage III ticket and a Vintage I ticket, (ii) two Vintage II tickets, or (iii) four Vintage I tickets. In fact, the descriptive statistics reported in Table 1 reveal that monetary payments in all of these cases, (i), (ii), and (iii), are more expensive than those of options (d-IV) and (d-V), and buyers do not have an economic incentive to engage in such separate purchases.

Next, a type-c buyer (who has a demand of three train rides) with a buyer index i' has three utility options:

$$
\begin{aligned}
U_{c,i'}^{\text{V,New}} &= V_{c,i'} - \overline{P}^{\text{V,New}} + \mathbb{EP}_t^{\text{II}} - \mathit{Resale}_t && (c\text{-V})\\
U_{c,i'}^{\text{IV}} &= V_{c,i'} - P_t^{\text{IV}} - \mathit{Search}_t + \mathbb{EP}_t^{\text{I}} - \mathit{Resale}_t && (c\text{-IV})\\
U_{c,i'}^{\text{III}} &= V_{c,i'} - P_t^{\text{III}} - \mathit{Search}_t - \mathit{Scrap}. && (c\text{-III})
\end{aligned}
$$

In our specifications of utility functions, not only for a type c buyer but also for any type of buyer, we have a committed resale market search process. This implies that, after the search-and-bidding process, a buyer who decides to search in the online resale market is eventually matched with a seller by the end of period t. For this reason, there is no continuation valuation in Equations (c-IV) and (c-III), which simplifies the model and enables us to obtain analytic resale price and welfare solutions.[18]

Similarly, a type-b buyer (who has a demand of two train rides) with a buyer index i'' has four utility options:

$$
\begin{aligned}
U_{b,i''}^{\text{V,New}} &= V_{b,i''} - \overline{P}^{\text{V,New}} + \mathbb{EP}_t^{\text{III}} - \mathit{Resale}_t && (b\text{-V})\\
U_{b,i''}^{\text{IV}} &= V_{b,i''} - P_t^{\text{IV}} - \mathit{Search}_t + \mathbb{EP}_t^{\text{II}} - \mathit{Resale}_t && (b\text{-IV})\\
U_{b,i''}^{\text{III}} &= V_{b,i''} - P_t^{\text{III}} - \mathit{Search}_t + \mathbb{EP}_t^{\text{I}} - \mathit{Resale}_t && (b\text{-III})\\
U_{b,i''}^{\text{II}} &= V_{b,i''} - P_t^{\text{II}} - \mathit{Search}_t - \mathit{Scrap}. && (b\text{-II})
\end{aligned}
$$

[17] The stochastic usage extension of the model is reported in the Online Appendix. Also, in our counterfactual experiment (Section 5), we also consider type-e users (who demand five rides each), as well as type-f (six rides) and type-g (seven rides) users.

[18] The supporting points for this buyer-side perfect matching are as follows. First, although online buyers are committed in their resale market search, they are not committed to searching within a specific vintage of resalable goods. In the specific case above, a type c buyer i' can search in both Vintage IV and III ticket resale markets, providing flexibility in her search process. Second, although we make a restriction of a perfect matching process from the view point of buyers, we allow for imperfect matching from the perspective of online sellers. In other words, the number of online sellers are allowed to be greater than the number of buyers in this online resale market. Third, we have an exogenous arriving and supply process of online sellers in the sub-market of Yahoo! Auctions resale market, which is governed by the entire resale market clearing condition. According to the format of Yahoo! Auctions, sellers first enter the market and post their auctioned products with sufficient auction time lengths, and then buyers decide to participate in such auctions. A typical auction takes a few days, and there is sufficient time for allowing potential buyers to enter the Yahoo! Auctions resale market. Thus, potential online buyers could stop from entering the Yahoo! Auctions online market when they observe that there is already a sufficient number of online buyers.

Lastly, a type-a buyer (who has a demand of only one train ride) with a buyer index i''' has five utility options:

$$\begin{array}{lcllllllllll}
U^{\mathrm{V,New}}_{a,i'''} & = & V_{a,i'''} & - & \overline{P}^{\mathrm{V,New}} & & & + & \mathbb{EP}^{\mathrm{IV}}_t & - & Resale_t & & & (a\text{-V}) \\
U^{\mathrm{IV}}_{a,i'''} & = & V_{a,i'''} & - & P^{\mathrm{IV}}_t & - & Search_t & + & \mathbb{EP}^{\mathrm{III}}_t & - & Resale_t & & & (a\text{-IV}) \\
U^{\mathrm{III}}_{a,i'''} & = & V_{a,i'''} & - & P^{\mathrm{III}}_t & - & Search_t & + & \mathbb{EP}^{\mathrm{II}}_t & - & Resale_t & & & (a\text{-III}) \\
U^{\mathrm{II}}_{a,i'''} & = & V_{a,i'''} & - & P^{\mathrm{II}}_t & - & Search_t & + & \mathbb{EP}^{\mathrm{I}}_t & - & Resale_t & & & (a\text{-II}) \\
U^{\mathrm{I}}_{a,i'''} & = & V_{a,i'''} & - & P^{\mathrm{I}}_t & - & Search_t & & & & & - & Scrap. & (a\text{-I})
\end{array}$$

Following the tradition set by preceding resale market studies, such as Esteban and Shum (2007), Chen et al. (2013), and Gavazza et al. (2014), we now model the competitive and price-taking resale market. Specifically, we propose the following setting for the sake of simplifying individual-level welfare analyses and empirical investigations.

Assumption 1 - *Competitive price-taking rational expectation equilibrium with no arbitrage*
The resale markets are competitive, and market participants who form rational expectations (Muth 1961) are price takers. In an equilibrium, there is no arbitrage opportunity.

Accordingly, a buyer gets the same utility regardless of her new- or used-good purchasing choice. It should be emphasized that the no-arbitrage condition is applied not only at the Yahoo! Auctions sub-market level but also at the entire resale market system level. Above, we use the minimalistic subset of the entire market level no-arbitrage condition that is enough to estimate online market resale friction costs and conduct a welfare analysis. Specifically, the well-known study of Werner (1987) shows that the existence of a price system that allows no-arbitrage is a necessary and sufficient condition of the existence of a competitive equilibrium. Thus, we have the market clearing condition not at the sub-market level, but at the entire resale market level. This entire-market no-arbitrage condition is further explored when we investigate welfare implications in Subsection 3.3.

Given Assumption 1, we can construct an indifference condition system by equating within-a-buyer-type utility options. We have one indifference condition equation based on type-d buyer's utility options, three equations based on type-c, six based on type-b, and ten based on type-a. The exact form of this indifference condition system is written as follows.[19] Note that valuation terms ($V_{d,i}, V_{c,i'}, V_{b,i''}$, and $V_{a,i'''}$) are canceled out as we are analyzing perfectly substitutable goods.

$$\begin{array}{llllllllcll}
-P^{\mathrm{IV}}_t & & & & & & & -\mathbb{EP}^{\mathrm{I}}_t & = & -\overline{P}^{\mathrm{V,New}} + Search_t - Resale_t + Scrap & (d\text{-IV}) = (d\text{-V}) \\
\hdashline
-P^{\mathrm{IV}}_t & & & & & & -\mathbb{EP}^{\mathrm{II}}_t & +\mathbb{EP}^{\mathrm{I}}_t & = & -\overline{P}^{\mathrm{V,New}} + Search_t & (c\text{-IV}) = (c\text{-V}) \\
 & -P^{\mathrm{III}}_t & & & & & -\mathbb{EP}^{\mathrm{II}}_t & & = & -\overline{P}^{\mathrm{V,New}} + Search_t - Resale_t + Scrap & (c\text{-III}) = (c\text{-V}) \\
P^{\mathrm{IV}}_t & -P^{\mathrm{III}}_t & & & & & & -\mathbb{EP}^{\mathrm{I}}_t & = & - Resale_t + Scrap & (c\text{-III}) = (c\text{-IV}) \\
\hdashline
-P^{\mathrm{IV}}_t & & & & & -\mathbb{EP}^{\mathrm{III}}_t & +\mathbb{EP}^{\mathrm{II}}_t & & = & -\overline{P}^{\mathrm{V,New}} + Search_t & (b\text{-IV}) = (b\text{-V}) \\
 & -P^{\mathrm{III}}_t & & & & -\mathbb{EP}^{\mathrm{III}}_t & & +\mathbb{EP}^{\mathrm{I}}_t & = & -\overline{P}^{\mathrm{V,New}} + Search_t & (b\text{-III}) = (b\text{-V}) \\
 & & -P^{\mathrm{II}}_t & & & -\mathbb{EP}^{\mathrm{III}}_t & & & = & -\overline{P}^{\mathrm{V,New}} + Search_t - Resale_t + Scrap & (b\text{-II}) = (b\text{-V}) \\
P^{\mathrm{IV}}_t & -P^{\mathrm{III}}_t & & & & & -\mathbb{EP}^{\mathrm{II}}_t & +\mathbb{EP}^{\mathrm{I}}_t & = & & (b\text{-III}) = (b\text{-IV}) \\
P^{\mathrm{IV}}_t & & -P^{\mathrm{II}}_t & & & & -\mathbb{EP}^{\mathrm{II}}_t & & = & - Resale_t + Scrap & (b\text{-II}) = (b\text{-IV}) \\
 & P^{\mathrm{III}}_t & -P^{\mathrm{II}}_t & & & & & -\mathbb{EP}^{\mathrm{I}}_t & = & - Resale_t + Scrap & (b\text{-II}) = (b\text{-III}) \\
\hdashline
-P^{\mathrm{IV}}_t & & & & -\mathbb{EP}^{\mathrm{IV}}_t & +\mathbb{EP}^{\mathrm{III}}_t & & & = & -\overline{P}^{\mathrm{V,New}} + Search_t & (a\text{-IV}) = (a\text{-V}) \\
 & -P^{\mathrm{III}}_t & & & -\mathbb{EP}^{\mathrm{IV}}_t & & +\mathbb{EP}^{\mathrm{II}}_t & & = & -\overline{P}^{\mathrm{V,New}} + Search_t & (a\text{-III}) = (a\text{-V}) \\
 & & -P^{\mathrm{II}}_t & & -\mathbb{EP}^{\mathrm{IV}}_t & & & +\mathbb{EP}^{\mathrm{I}}_t & = & -\overline{P}^{\mathrm{V,New}} + Search_t & (a\text{-II}) = (a\text{-V}) \\
 & & & -P^{\mathrm{I}}_t & -\mathbb{EP}^{\mathrm{IV}}_t & & & & = & -\overline{P}^{\mathrm{V,New}} + Search_t - Resale_t + Scrap & (a\text{-I}) = (a\text{-V}) \\
P^{\mathrm{IV}}_t & -P^{\mathrm{III}}_t & & & & -\mathbb{EP}^{\mathrm{III}}_t & +\mathbb{EP}^{\mathrm{II}}_t & & = & & (a\text{-III}) = (a\text{-IV}) \\
P^{\mathrm{IV}}_t & & -P^{\mathrm{II}}_t & & & -\mathbb{EP}^{\mathrm{III}}_t & & +\mathbb{EP}^{\mathrm{I}}_t & = & & (a\text{-II}) = (a\text{-IV}) \\
P^{\mathrm{IV}}_t & & & -P^{\mathrm{I}}_t & & -\mathbb{EP}^{\mathrm{III}}_t & & & = & - Resale_t + Scrap & (a\text{-I}) = (a\text{-IV}) \\
 & P^{\mathrm{III}}_t & -P^{\mathrm{II}}_t & & & & -\mathbb{EP}^{\mathrm{II}}_t & +\mathbb{EP}^{\mathrm{I}}_t & = & & (a\text{-II}) = (a\text{-III}) \\
 & P^{\mathrm{III}}_t & & -P^{\mathrm{I}}_t & & & -\mathbb{EP}^{\mathrm{II}}_t & & = & - Resale_t + Scrap & (a\text{-I}) = (a\text{-III}) \\
 & & P^{\mathrm{II}}_t & -P^{\mathrm{I}}_t & & & & -\mathbb{EP}^{\mathrm{I}}_t & = & - Resale_t + Scrap. & (a\text{-I}) = (a\text{-II})
\end{array}$$

[19] The left hand side (LHS) of the system equations represents the variables of resale market prices determined at the Yahoo! Auctions market level, while the right hand side variables are exogenously determined at the entire resale market system level. Under the stationary ($P^k = \mathbb{EP}^k$) condition, the rank and the number of unknown variables in the left hand side matrix are both four, indicating a unique solution. On the other hand, under the non-stationary (P^k differs from $\mathbb{EP}^k$) condition, the rank of the left hand side matrix is seven with eight unknown variables, indicating that a general solution has one free parameter variable, which has sub-market structure interpretations. See Observation 2 for a general solution. In the right hand side (RHS) of the system equation, the existence of solutions (for both stationary and non-stationary ones) requires the condition that rank(LHS) = rank(LHS,RHS). Accordingly, homogeneous buyer-side search and seller-side resale costs (across user types) are essential to obtain analytic solutions.

3.2 Observations and individual-level welfare implications

The indifference condition system provides the following observations and proposition.[20] Before proceeding, the distinction between exogenous and endogenous variables to the Yahoo! Auctions resale market should be clearly mentioned. In the no-arbitrage and price-taking equilibrium, the market friction costs ($Search_t$, $Resale_t$, $Scrap$, and later described E_t) are exogenously governed at the entire resale market level. This exogeneity is founded on the arrival process of sellers (and subsequent entry of buyers) into Yahoo! Auctions with the market clearing condition, which is determined at the entire resale market system level. On the other hand, online resale market prices (P_t^ks and $\mathbb{EP}_t^k$s) are determined in the Yahoo! Auctions platform resale market, a small sub-market of the entire resale market system. The solution of the no-arbitrage indifference condition system is summarized by the following observation.

Observation 2 - *Competitive resale market prices*
If $P_t^k \neq \mathbb{EP}_t^k$ for $k \in \{I, II, III, IV\}$, non-stationary equilibrium resale market prices are

$$\begin{bmatrix} P_t^{\mathrm{IV}} \\ P_t^{\mathrm{III}} \\ P_t^{\mathrm{II}} \\ P_t^{\mathrm{I}} \\ \mathbb{EP}_t^{\mathrm{IV}} \\ \mathbb{EP}_t^{\mathrm{III}} \\ \mathbb{EP}_t^{\mathrm{II}} \\ \mathbb{EP}_t^{\mathrm{I}} \end{bmatrix} = \begin{bmatrix} 4/5 \\ 3/5 \\ 2/5 \\ 1/5 \\ 4/5 \\ 3/5 \\ 2/5 \\ 1/5 \end{bmatrix} \overline{P}^{V,New} - \begin{bmatrix} 4/5 \\ 3/5 \\ 2/5 \\ 1/5 \\ 4/5 \\ 3/5 \\ 2/5 \\ 1/5 \end{bmatrix} Search_t + \begin{bmatrix} 1/5 \\ 2/5 \\ 3/5 \\ 4/5 \\ 1/5 \\ 2/5 \\ 3/5 \\ 4/5 \end{bmatrix} Resale_t - \begin{bmatrix} 1/5 \\ 2/5 \\ 3/5 \\ 4/5 \\ 1/5 \\ 2/5 \\ 3/5 \\ 4/5 \end{bmatrix} Scrap + \begin{bmatrix} 1/5 \\ 2/5 \\ 3/5 \\ 4/5 \\ -4/5 \\ -3/5 \\ -2/5 \\ -1/5 \end{bmatrix} E_t, \tag{1}$$

where $E_t \in \mathbb{R}\}$ is a scalar variable.

In the above observation, if $E_t = 0$, the equivalence of $P_t^k = \mathbb{EP}_t^k$ for $k \in \{\mathrm{I, II, III, IV}\}$ realizes. Furthermore, if the resale market friction costs are also all zero, the equilibrium resale market prices collapse to $P_t^k = \mathbb{EP}_t^k = \frac{k}{5}\overline{P}_t^{\mathrm{V,New}} (= P^{k,\mathrm{Theo}})$, which is proportional to the remaining usage. Thus, we provide the equilibrium foundation for the theoretical prices that are introduced in the descriptive statistics section and plotted in Figure 2.

The above analytic solution system has three exogenous opportunity costs ($Search_t$, $Resale_t$, and $Scrap$) and one variable E_t that have price-taking and sub-market equilibrium insights, as they characterize different equilibrium information. In an equilibrium, $Search_t$ is related to the bidder-seller ratio at period t and measuring the current difficulty to obtain an auctioned object. $Resale_t$ is related to the (inverse of the) bidder-seller ratio at the reselling period, measuring the future difficulty of online resale. Next, E_t measures an intertemporal price gap between current and resale period market prices with the no-arbitrage condition. E_t is determined by the competitive equilibrium framework of the entire resale market system, and the Yahoo! Auctions market is a small sub-market that treats E_t as exogenously given. However, such price gaps cannot be arbitrary, as any gap that does not follow the coefficients of E_t in Equation (1) generates an arbitrage opportunity among buyers. Importantly, E_t is invariant to the arguments of resale price distortions and individual-level welfare loss described later. The coefficient vectors of Equation (1) provides the following identification conditions for empirical work.[21]

Observation 3 - *Identification*
$Resale_t$ and $Scrap$ are not separately identified. However, in the special case of a fixed scrap cost, $Resale_t$ is identified.

Next, we investigate resale market price distortions caused by friction costs. Based on Equation (1), we can compare the resale market prices with and without market frictions, calculating a price gap between the cases of (i) $Search_t = Resale_t = Scrap = 0$ and (ii) $Search_t,\ Resale_t,\ Scrap > 0$. The following observation summarizes the implications, and notably this observation is invariant to E_t.

[20]The proofs in this subsection are omitted as they are trivially derived with the introductory-level linear algebra.

[21]Our non-identification result implies that the price data alone is not enough to separately identify the resale and scrap costs, and researchers need to fix one of them to identify the other. This non-identification result is compatible with the assumptions made by the zero (or negligibly small) resale transaction cost in the resalable goods literature (e.g. Esteban and Shum 2007 and Jacobsen and Van Benthem 2015). Mathematically, in Equation (1), the coefficient vectors of $Resale_t$ and $Scrap$ are the same direction in the vector space, and resale market prices do not have sufficient information to separately identify both of them. Thus, the $1 increase in resale cost and $1 decrease in scrap cost have the same effect on sub-market resale market prices. This non-identification is intuitive since after her usage, a resalable good user must either resell a good or scrap it.

Table 2: Individual-level utility losses.

User type	Utility in frictionless resale markets	Utility in frictional markets ($Search_t > 0$, $Resale_t > 0$, and $Scrap > 0$)	Utility loss caused by resale market frictions
e: demanding five train rides	$V_e - \frac{5}{5}P^{\text{V,New}} - \frac{0}{5}E_t$	$V_e - \frac{5}{5}P^{\text{V,New}} - \frac{0}{5}Search_t - \frac{0}{5}Resale_t - \frac{5}{5}Scrap - \frac{0}{5}E_t$	$-\frac{0}{5}Search_t - \frac{0}{5}Resale_t - \frac{5}{5}Scrap$
d: ...... four	$V_d - \frac{4}{5}P^{\text{V,New}} - \frac{1}{5}E_t$	$V_d - \frac{4}{5}P^{\text{V,New}} - \frac{1}{5}Search_t - \frac{1}{5}Resale_t - \frac{4}{5}Scrap - \frac{1}{5}E_t$	$-\frac{1}{5}Search_t - \frac{1}{5}Resale_t - \frac{4}{5}Scrap$
c: ...... three	$V_c - \frac{3}{5}P^{\text{V,New}} - \frac{2}{5}E_t$	$V_c - \frac{3}{5}P^{\text{V,New}} - \frac{2}{5}Search_t - \frac{2}{5}Resale_t - \frac{3}{5}Scrap - \frac{2}{5}E_t$	$-\frac{2}{5}Search_t - \frac{2}{5}Resale_t - \frac{3}{5}Scrap$
b: ...... two	$V_b - \frac{2}{5}P^{\text{V,New}} - \frac{3}{5}E_t$	$V_b - \frac{2}{5}P^{\text{V,New}} - \frac{3}{5}Search_t - \frac{3}{5}Resale_t - \frac{2}{5}Scrap - \frac{3}{5}E_t$	$-\frac{3}{5}Search_t - \frac{3}{5}Resale_t - \frac{2}{5}Scrap$
a: ...... one	$V_a - \frac{1}{5}P^{\text{V,New}} - \frac{4}{5}E_t$	$V_a - \frac{1}{5}P^{\text{V,New}} - \frac{4}{5}Search_t - \frac{4}{5}Resale_t - \frac{1}{5}Scrap - \frac{4}{5}E_t$	$-\frac{4}{5}Search_t - \frac{4}{5}Resale_t - \frac{1}{5}Scrap$

A type-e buyer who has a demand of five train rides is added for comparison.

Observation 4 - *Mixed directions of resale price distortions*
The resale market price distortion for a vintage $k \in \{\text{I, II, III, IV}\}$ ticket created by friction costs is

$$ResalePriceDistortion_t(k) = -\frac{k}{5}Search_t + \frac{5-k}{5}Resale_t - \frac{5-k}{5}Scrap. \tag{2}$$

Observation 4 explains the observed price distortions in Figure 2. As a simple example, if we hypothetically assume $Search_t = Resale_t$ and $Scrap = 0$, Equation (2) becomes $ResalePriceDistortion_t(k) = \frac{5-2k}{5}Search_t$, which is positive with $k \in \{\text{I, II}\}$, while it is negative with $k \in \{\text{III, IV}\}$. Alternatively, if $Search_t = Scrap = 0$ and $Resale > 0$, the equation collapses to $ResalePriceDistortion_t(k) = \frac{5-k}{5}Resale_t$, which could be interpreted as a resale-avoidance premium: a resold ticket with a low degree vintage (e.g. $k \in \{\text{I, II}\}$) has a relatively large upward price distortion, and is more likely to be used up, as a using-up buyer is able to avoid a resale transaction cost.

Also, Observation 4 indicates that a positive or negative direction of resale price distortion, in general, depends on the size of the friction costs. Thus, an empirical estimation is required for understanding the causes of such price distortions and investigating welfare implications.

Next, by assigning the equilibrium resale market prices in Equation (1) to the utility functions [(d-V) to (a-I)], we can derive the individual user level utility losses caused by resale market friction costs. Table 2 summarizes the findings of welfare distortions. The second column reports utilities achieved with hypothetical frictionless resale market prices, while the third column addresses utilities attained with frictional resale market prices. The last column depicts the gaps between utilities obtained from frictionless and frictional resale markets, deriving the following proposition that will be the basis of our welfare analyses.[22] Note that, similar to Observation 4, the proposition is invariant to the values of E_t and associated (non-)stationary status.

Proposition 5 - *Individual-level welfare loss*
The individual level utility loss caused by the resale market friction costs to a resalable goods user who demands a degree of D usage is

$$WelfareLoss_t(D) = -\underbrace{\frac{5-D}{5}}_{\text{reversely-proportional}}Search_t - \underbrace{\frac{5-D}{5}}_{\text{reversely-proportional}}Resale_t - \underbrace{\frac{D}{5}}_{\text{proportional}}Scrap, \tag{3}$$

where $D \in \{1,2,3,4,5\}$ is a demanded resalable good usage index.

With the emphasis on the resale transaction externalities, we have the following economic intuitions regarding the coefficients in Equation (3). The coefficients of $Search_t$ and $Resale_t$ are reversely proportional as a user who consumes a large degree of usage creates a smaller degree of resale market negative externality through the life of a resalable good. As an extreme example, a user who consumes five usages does not create any resale market transaction related externality and does not bear any welfare loss related to search and resale costs. On the other hand, the coefficient of $Scrap$ is proportional because a user who intends to consume a large degree of usage contributes to generating a larger scrapping cost externality on a terminal user after a resale transfer, compared to a user who consumes a smaller degree of usage.[23]

[22] It is counterfactually posited that resale markets with and without friction costs share the same value of E_t. This counterfactual argument is legitimate since we base our argument on the sub-market analysis in which the online resale market has negligible influence on the entire resale market and does not affect the exogenously given E_t.

[23] To allow stochastic usage of resalable goods, we report the stochastic version of Proposition 5 in the Online Appendix, in which buyers stochastically plan their rides.

Figure 7: Frictionless resale markets.

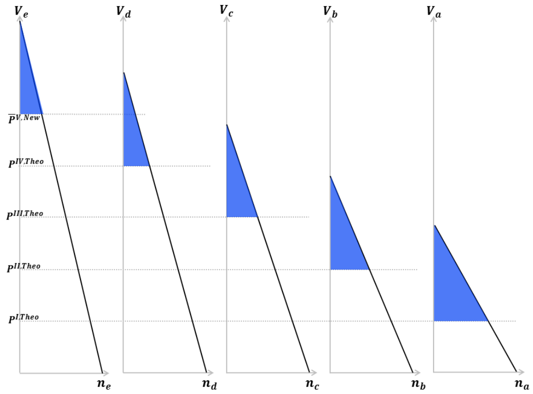


Figure 8: Resale market prohibition.

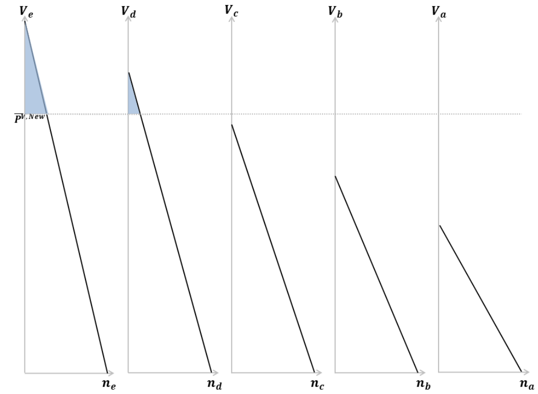


Figure 9: Frictional resale markets.

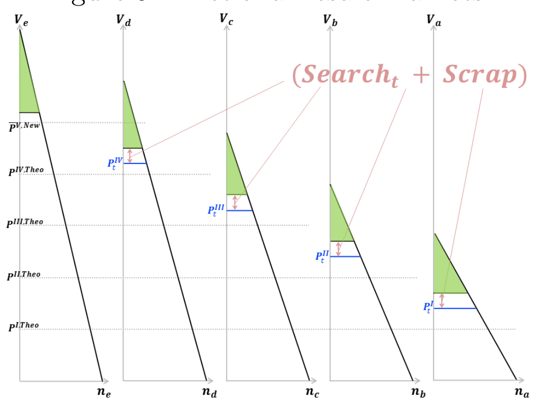
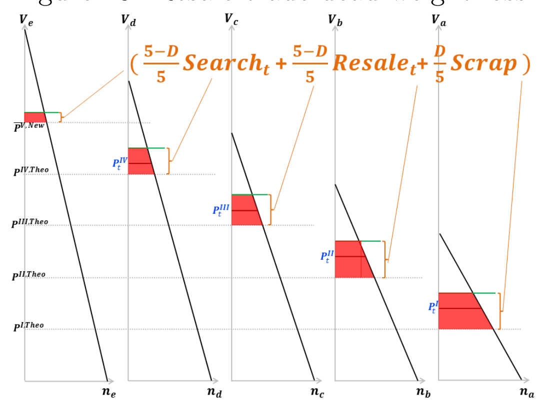


Figure 10: Resale trade dead-weight loss.



3.3 Heterogeneous welfare effects of resale market friction costs

Thanks to the commoditized and perfectly-substitutable nature of the goods, the findings in individual-user-level welfare losses can be translated into a welfare analysis, as the no-arbitrage condition applies at the entire market level. In each of Figures 7 to 10, the demand of a type-e user (who demands five usages) is drawn at the left-most position, that of a type-d (who demands four usages) is second from the left, and other types of buyers' demands are illustrated in the same way. These figures are based on the stationary equilibrium (i.e. $P_t^k = \mathbb{E}\mathbb{P}_t^k$ and $E_t = 0$), yet the figures can easily be converted to the non-stationary equivalent.[24] Note that these figures are for describing welfare among resalable good users and not for describing markets for each vintage of resalable goods. For this reason, the vertical axes describe willingness-to-pay, while the horizontal axes denote the number of each type of users. We use the notations of n_e, n_d, n_c, n_b, and n_a for describing the number of each type of users. Figure 7 shows the welfare gain that could be generated in frictionless resale markets. The theoretical prices are proportional to the remaining usage of resalable goods. However, as characterized in Proposition 5, the existence of resale market friction costs dwarfs welfare gains, as represented in Figure 9. The structure of welfare loss is two-fold. The first and direct loss is caused by disutility resulting from resale market friction costs in a buyer's utility function. The second loss is caused by changes in resale prices. Note that this second loss could be positive or negative as described by the mixed price distortions direction in Observation 4, although the combination of the first and second losses are non-positive, as listed in Table 2. Note also that in Figure 9, in addition to payment through distorted online resale market prices, there is further individual-level welfare loss of $(Search_t + Scrap)$, which directly appears in the utility options of (d-IV), (c-III), (b-II), and (a-I). The resale market dead-weight losses are illustrated in Figure 10, and the height of loss within each type of demand is characterized in Proposition 5. Lastly, Figure 8 depicts the prohibition of resale trades, which restricts any means of resale opportunities. Under the prohibition, only the users who have considerably high willingness-to-pay can afford goods. The difference between Figure 7 and 8 illustrates the welfare gain from the opening of a resale market.[25]

[24]To do this, we replace $P_t^{k,\text{theo}}$ with $(P_t^{k,\text{theo}} + \frac{k}{5}E_t)$ for $k \in \{\text{I, II, III, IV}\}$ in Figures 7 to 10.

[25]The Online Appendix reports a further graphical explanation about the welfare gains generated through the opening of a frictional resale market.

4 Estimation methods and results

This section describes the GMM estimation based on the closed-form resale market prices of Equation (1). First, we illustrate the periods and terms of our empirical investigation. Second, we provide descriptions regarding the three different constructions of expected resale prices. Lastly, we report the estimation results and discuss model specifications.

4.1 Estimation periods and terms

For our empirical investigation, we use the data for periods $t = 2 \sim 43$ (July 21st $\sim$ August 31st, 42 days). We eliminate the initial period ($t = 1$, July 20th) and the periods after period $t = 44$ (after September 1st) for the following reasons: First, the trading volume of the initial period is observed to be thin. This is because some usage time is required to allow new goods to be converted to used goods. Subsequently, a competitive price-taking environment may not be fostered due to the scarcity of used goods in the resale markets. Second, JR ceases new ticket sales for periods $t = 44 \sim 53$ (September 1st - 10th), resulting in the entire resale market system losing access to new tickets. As the primary goal of this study is investigating the welfare structure of a competitive resale market with unrestricted access to new resalable goods (such as mobile phones, tablets, and textbooks), we also exclude these periods. Note that our rational expectation model ($t = 2 \sim 43$) is compatible with this termination of the new goods supply, as far as buyers form rational expectations of expected resale prices.

Next, as described in Table 1 and Figures 5 to 6, the market congestion greatly changes throughout the season. Accordingly, we estimate structural parameters by term, which is defined in Table 1. Specifically, we provide the estimation results of six terms (Term ① to ⑥) side-by-side for comparison, and report a correlation between estimated friction costs and market congestion.

4.2 Empirical constructions of expected resale prices

The construction of the expected resale prices at period t, denoted as $\mathbb{EP}_t^k$ where $k \in \{\text{I}, \text{II}, \text{III}, \text{IV}\}$, plays a crucial role in our empirical investigations. Ideally, researchers could use individual-and-transaction-level data that tracks all purchasing and reselling records throughout the birth and death of the market. This data, though, is seldom available to researchers. Therefore, we construct three different types of expected prices that could be considered as reasonable alternative measurements with which researchers are able to conduct resalable goods related research even when data is limited: (A) average subsequent transacted price; (B) after-seven-period average subsequent transacted price; and (C) after-seven-period price constructions. All of these expected resale prices are adjusted by a platform charge.

The first construction, which we call "(A) average subsequent transacted price," calculates an expected resale price in the following simple fashion of

$$\mathbb{EP}_t^k = \frac{1 - \tau_{\text{Platform}}}{Q_{t,\text{After}}^k} \sum_{a=t+1}^{\overline{T}} \sum_{j=1}^{TS_a^k} p_{a,j}, \qquad [\mathbb{EP}\text{ Construction (A)}]$$

where $a \in \{t+1, \cdots, \overline{T}\}$ is the index for periods after the period $t+1$, TS_a^k is the number of transacted supplies of vintage $k \in \{\text{I, II, III, IV}\}$ tickets at period a (which is described in Table 1 and Figure 3), τ_{Platform} is the platform charge for a transaction, $Q_{t,\text{After}}^k = \sum_{a=t+1}^{\overline{T}} TS_a^k$ is the number of observed transacted supplies of vintage k tickets recorded after period $t+1$, $p_{a,j}^k$ is the recorded transacted price, $j \in \{1, \cdots, TS_a^k\}$ is the transaction index, and $\overline{T} = 53$ is the ticket expiring period. The term $1 - \tau_{\text{Platform}}$ is multiplied, as Yahoo! Auction charges a seller the transaction margin of $\tau_{\text{Platform}} = 0.054$, while it does not charge on buyers anything. See the Online Appendix for further discussions on taxes and transaction charges. Intuitively, this definition assumes that a user who buys a ticket today has the intention of reselling it later based on the empirically observed resale transaction frequency. The expected prices under this construction are plotted in Figure 11, and we observe flat yet gradually decreasing trends. Next, the second construction, which we label "(B) after-seven-period average subsequent transacted price," allows a user to have a seven-day traveling period, defined by

$$\mathbb{EP}_t^k = \frac{1 - \tau_{\text{Platform}}}{Q_{t,\text{After7}}^k} \sum_{a=t+7}^{\overline{T}} \sum_{j=1}^{TS_a^k} p_{a,j}. \qquad [\mathbb{EP}\text{ Construction (B)}]$$

Figure 11: $\mathbb{EP}$ construction (A): Average subsequent transaction prices.

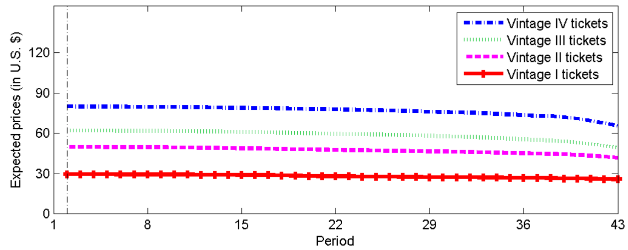
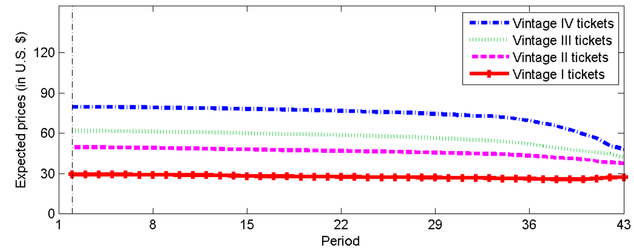


Figure 12: $\mathbb{EP}$ construction (B): After-seven-periods average subsequent transaction prices.



We set a seven-period span to reflect an approximate traveling time that a user will spend before returning to the resale market. Figure 12 illustrates the expected prices under this construction. The major difference between Figures 11 and 12 is that, at the end of the season, expected prices of Vintage IV, III, and II plunge more sharply, which may affect estimation results. Finally, the last construction, which we name "(C) after-seven-period price," that a reseller finishes her resale transaction one week after she purchases it, is defined by

$$\mathbb{EP}_t^k = (1 - \tau_{\text{Platform}}) \cdot P_{t+7}^k. \qquad [\mathbb{EP} \text{ Construction (C)}]$$

See Figure 2 for these after-seven-period prices. Although this construction is ad-hoc and specific in terms of the resale timing, it will be used later for a robustness check of resale-market friction costs estimates.

4.3 Estimation method and results

Given the above constructions of expected prices and terms, we apply the two-step GMM estimation method to the closed-form resale market prices of Equation (1). As observed prices within each ticket vintage are time series data, serial correlations are naturally expected to emerge. For this reason, we apply the Heteroskedasticity Autocorrelation Consistent (HAC) method for calculating weight matrices and standard errors. Specifically, we apply the Bartlett (Newey-West) kernel for computing covariance matrices. Note that this GMM estimation has eight moments and three estimating parameters. Thus, over-identification and model validity tests can be examined with the five degrees of freedom. Also, we exclude the term of $Scrap$, which is set at zero throughout our empirical investigation.

The estimation results under $\mathbb{EP}$ Construction (A) are listed in Table 3. The results under Construction (B) and (C) are quite similar and listed in the Online Appendix. In general, the model fits the data well, as none of the over-identification tests are rejected with a conservative significance level. Thus, our structural model is not rejected by the data. In addition, all coefficients are significant, and the hypotheses of zero friction costs are easily rejected for both $Search_t$ and $Resale_t$.

The estimates of bidder-side costs ($Search_t$s) in Table 3 are comparable to those reported in preceding studies investigating eBay auctions. For example, Bajari and Hortacsu (2003) estimate the bidding cost for collectible coins is \$3.20 (≈€2.56 ≈£2.03), which is much lower than our estimates. However, the collectible coins are somehow recreational items, and bidders may have a joy-of-bidding preference, which could mitigate bidding costs. Sailer (2006) reports that the bidding cost is \$16.47 (≈€13.19 ≈£10.42) for PDA devices. Recently, Bodoh-Creed et al. (2016) report that the average participation cost for an Amazon Kindle device sold on eBay auctions is slightly lower than \$10 (≈€8.01 ≈£6.33). Despite the fact that environments are slightly different in terms of auctioned items and bidder-seller ratios, the latter two broadly agree with our estimates.

The estimates of friction costs are plotted in Figure 13 over the terms of ① to ⑥. Under all $\mathbb{EP}$ Constructions (A), (B), and (C), we observe four major findings: (i) throughout the periods, both search and resale costs are large, ranging from \$5 to \$27, indicating the importance of modeling two-sided friction costs in platform research; (ii) $Search_t$ is increasing, especially during the last three terms ($t = 23 \sim 43$); (iii) $Resale_t$ is gradually decreasing over periods; and (iv) except for the estimates of $Resale_t$ under Construction (C) for the first two periods ($t = 2 \sim 22$), three $\mathbb{EP}$ constructions provide similar qualitative and quantitative estimation results.[26,]

[26] There are two reasons for the large $Resale_t$ estimates under $\mathbb{EP}$ Construction (C) for the first three periods. First, observed prices are gradually decreasing before crashing. Thus, the $\mathbb{EP}_t^k = P_{t+7}^k$ construction provides the highest expected resale prices during these

Table 3: Estimation results: Based on $\mathbb{EP}$ construction (A).

	Term ①	②	③	④	⑤	⑥
$Search_t$	\$6.280***	\$7.349***	\$9.686***	\$14.10***	\$19.03***	\$22.21***
	(0.144)	(0.0258)	(0.172)	(0.303)	(0.0880)	(0.260)
$Resale_t$	\$10.53***	\$11.18***	\$11.33***	\$9.517***	\$9.516***	\$8.618***
	(0.0201)	(0.0112)	(0.0188)	(0.00502)	(0.0628)	(0.0521)
E_t	12.23***	12.82***	12.59***	8.705***	6.837***	8.437***
	(0.144)	(0.132)	(0.141)	(0.171)	(0.101)	(0.114)
Num. of periods	7	7	7	7	7	7
Periods	2∼8	9∼15	16∼22	23∼29	30∼36	37∼43
J-statistic	1.877	1.828	1.981	1.909	1.711	1.799
(p-value)	(0.758)	(0.767)	(0.739)	(0.752)	(0.789)	(0.773)

Inside brackets are HAC estimates of standard errors with the Newey-West kernel.
*** indicates the significance with 1%, ** with 5%, and * with 10%.
Scrap is fixed at zero.

Table 4: Estimated individual-level welfare loss: $\mathbb{EP}$ construction (A).

User type	Term ①	②	③	④	⑤	⑥
e: demanding five rides	-\$0.00	-\$0.00	-\$0.00	-\$0.00	-\$0.00	-\$0.00
	(-0.0%)	(-0.0%)	(-0.0%)	(-0.0%)	(-0.0%)	(-0.0%)
d: demanding four rides	-\$3.36	-\$3.71	-\$4.20	-\$4.72	-\$5.71	-\$6.17
	(-2.8%)	(-3.1%)	(-3.5%)	(-4.0%)	(-4.8%)	(-5.2%)
c: demanding three rides	-\$6.72	-\$7.41	-\$8.41	-\$9.45	-\$11.42	-\$12.33
	(-5.7%)	(-6.3%)	(-7.1%)	(-8.0%)	(-9.6%)	(-10.4%)
b: demanding two rides	-\$10.09	-\$11.12	-\$12.61	-\$14.17	-\$17.13	-\$18.5
	(-8.5%)	(-9.4%)	(-10.6%)	(-12.0%)	(-14.5%)	(-15.6%)
a: demanding one ride	-\$13.45	-\$14.82	-\$16.82	-\$18.90	-\$22.84	-\$24.66
	(-11.3%)	(-12.5%)	(-14.2%)	(-15.9%)	(-19.3%)	(-20.8%)
Num. of periods	7	7	7	7	7	7
Periods	2∼8	9∼15	16∼22	23∼29	30∼36	37∼43

Inside parentheses are percentages of the new good price of \$118.5 (including tax).
A type-e buyer who demands five train rides is added for comparison.

The welfare-loss numbers in Table 4 could be comparable to the amount of time and opportunity cost a bidder (who will later be a seller) needs to spend on Yahoo! Auctions to make transactions, which captures their forgone opportunity cost. Specifically, the average part-time hourly wage in Japan, which the expected (college student) users of *Seishun-18-Kippu* tickets receive, was about \$10.40 dollars in August 2014.[27] Accordingly, the maximum foregone opportunity cost of -\$24.66 (the largest welfare loss in Table 4) corresponds to the part-time wages of 2.37 hours.

For the model fitness, we calculate L^1 and L^2 norms with the $\mathbb{EP}$ constructions of (A), (B), and (C).[28] Among them, we find that Construction (A) provides the lowest L^2 norm, indicating a relatively suitable model specification. For this reason, in the rest of this study, we primarily report the welfare analysis results based on Construction (A).

periods ($t = 2 \sim 22$). Second, among the bottom four equations of the moment condition in (1), which are related to expected resale prices, high expected resale prices result in a high resale cost. The economic intuition is that, under the no-arbitrage condition, a utility loss caused by a high resale cost is compensated by a higher resale price.

[27]The exchange rate is 1 USD = 100 Yen. Source: Ministry of Health, Labor, and Welfare (in Japanese, accessed on 2019, April 3rd) - `https://www.mhlw.go.jp/toukei/itiran/roudou/monthly/26/2608r/2608r.html`

[28]Fitted prices and L^1 and L^2 norms are reported in the Online Appendix.

Figure 13: Estimated search and resale costs (with $Scrap = 0$).

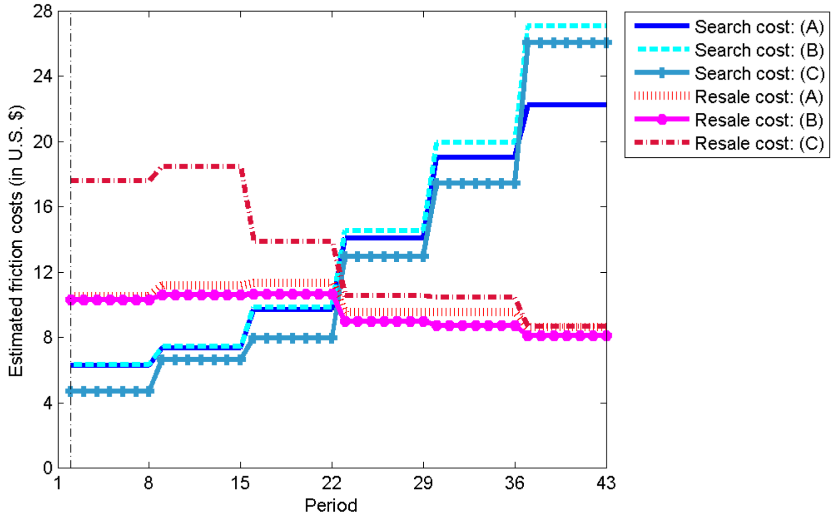
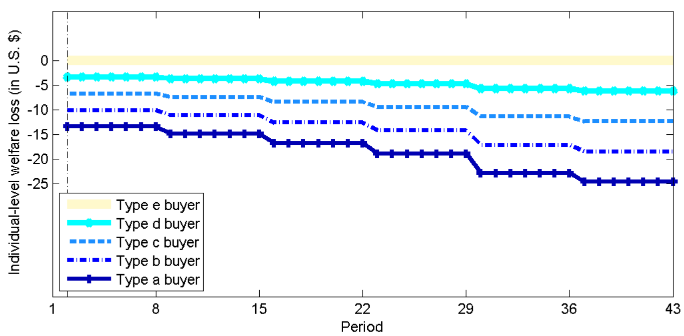


Figure 14: Estimated individual-level welfare loss by user type: $\mathbb{EP}$ construction (A).



5 Implications on welfare and counterfactual experiments

In this section, we first discuss individual-level welfare loss analyses caused by online resale market friction costs. As shown in Equation (3), the losses are heterogeneous and described as disadvantages for resalable goods users who intend to use a relatively small degree of usage, yet the size of heterogeneity is an empirical question. Second, we discuss the correlation between friction costs market congestion. Lastly, we conduct a counterfactual experiment of bundle-size designs.

5.1 Individual-level welfare implications

Based on the estimation results reported in Table 3, the heterogeneous and individual-user-level welfare-loss effects are calculated based on Equation (3) with estimated search and resale cost parameters under the expected resale price construction of (A).[29] The calculated welfare losses are listed in Table 4. In the table, we also report the percentages of welfare losses relative to the new good price of \$118.50 (including tax) in parentheses. The welfare losses are also plotted in Figure 14.

There are three major empirical findings in Table 4 and Figure 14. First, if resalable goods users do not intend to use up goods, the size of the welfare loss is large with the worst being -20.8% of the new good price.

[29]Individual-level welfare loss analyses based on Constructions (B) and (C) are found in the Online Appendix.

Figure 15: Normalized bidder-seller ratio, search cost, and resale cost: $\mathbb{EP}$ construction (A).

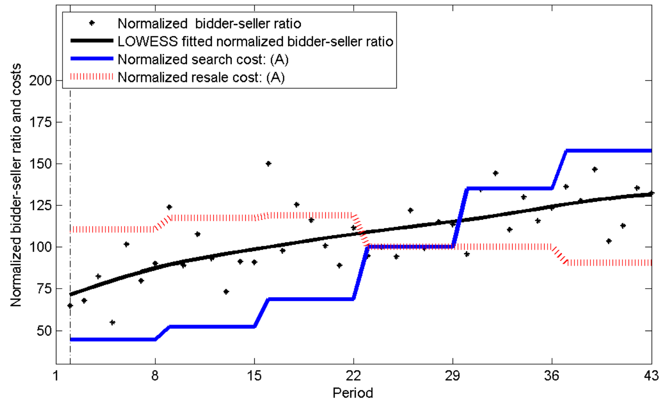


Table 5: Correlations: bidder-seller ratio and market friction costs: $\mathbb{EP}$ construction (A).

	R_t^{All}	$\widehat{R}_t^{\text{All,Fitted}}$
$\widehat{Search}_t$	0.658	0.917
$\widehat{Resale}_t$	-0.429	-0.706

Second, we empirically confirm that the size of the heterogeneity in welfare losses among user types is large, ranging from -\$3.36 (type-d in term ①) to -\$24.66 (type-a in term ⑥). This implies that the heights of resale-market dead-weight loss depicted in Figure 10 are non-negligibly high among users who intend to consume smaller degrees of usage. This finding further suggests the existence of users who are excluded from resale trading opportunities as they cannot bear with these welfare losses. Third, in our analyzed online resale market, welfare losses are gradually growing over periods, and they are connected to the market congestion in the next subsection.[30]

5.2 A discussion on market congestion and buyer-seller matching friction costs

One of the drawbacks of eBay or Yahoo! Auctions is a bidder-side search and bidding opportunity cost: a bidder may have to participate in many auctions before she/he obtains a desired object, and such processes are often time consuming. The objective of this subsection is to provide a discussion on market congestion and friction costs, as, to our knowledge, this study is the first to recover both buyer-side search and seller-side resale costs in an online platform. We base our argument on the observed bidder-seller ratio R_t^{All}, which is described in Table 1 and plotted in Figure 6, as it measures market congestion from the bidders' perspective at each period.

For simplifying the argument, we conduct normalization of the following three variables based on their middle-of-the-season values at period $t = 23$ (August 11th) being set at 100: (i) R_t^{All} of observed bidder-seller ratio for all vintages of tickets, (ii) $\widehat{Search}_t$ of estimated buyer-side search costs, and (iii) $\widehat{Resale}_t$ of estimated seller-side resale costs. The normalized values are plotted in Figure 15.[31] In the figure, we also add the LOWESS (Locally Weighted Scatterplot Smoothing) fitted values of observed bidder-seller ratio, denoted as $\widehat{R}_t^{\text{All,Fitted}}$.

Figure 15 depicts that the bidder-seller ratio is positively correlated with buyer-side search costs, while it is negatively correlated with seller-side resale costs. The correlation coefficients are calculated and listed in Table 5, and we observe mild correlations with respect to observed R_t^{All} and strong correlations in terms of fitted $\widehat{R}_t^{\text{All}}$. Thus, we empirically find that, in our analyzed online resale market, a congested market is associated with a higher buyer-side friction cost, while it is also associated with a lower seller-side friction cost. The preceding

[30] In addition, regarding the relative magnitude between the Vintage I ticket price (on average slightly above \$30) and the traveler's maximum welfare loss (-\$24.66), it could also be comparable to alternative transportation methods, which are more expensive. For comparison purposes, we collected inter-city bus and bullet train transportation prices for the Summer of 2018. For example, the daytime bus transportation service between two major cities (Tokyo-Osaka) costs about \$58 with 8.5 hours riding time (2018 data), while slower train travel with *Seishun-18-Kippu* ticket takes 10.5 hours. Thus, compared to a slow train trip, some consumers would pay about \$28 extra for saving 2 hours on a bus trip (and potentially for enjoying a comfortable seat). On the other hand, the single bullet train ride (Tokyo-Osaka) costs a traveler about \$136.20 with about 2.5 hours' travel time (2018 data). That is, some travelers pay about \$100 extra for saving 8 hours. These prices and time comparisons anecdotally support that the willingness-to-pay for transportation services is large in Japan during the summer season, and consumers can bear the welfare loss of -\$24.66.

[31] Observed and estimated values at $t = 23$ (August 11th) are $\widehat{R}_t^{\text{All}} = 6.83$, $\widehat{Search}_t = \$14.10$, and $\widehat{Search}_t = \$9.52$.

work of Gavazza (2011) reports that, in the commercial aircraft market, a thinner market is disadvantageous to sellers. Our finding in the online auction market is in line with his finding in terms of sellers. In addition, we find similar correlation numbers under $\mathbb{EP}$ Constructions (B) and (C), and they are listed in the Online Appendix. The correlations in Table 5 are intuitive. When the online auction market becomes congested, indicated by a high bidder-seller ratio (R_t^{All}), a bidder has to participate in more auctions to get a product, on average. Such increased participation inflates the opportunity costs among buyers. On the other hand, a high R_t^{All} is advantageous to a seller, as she is less likely to miss the opportunity to attract bidders and to sell her product in an online auction platform. To our knowledge, these market congestion and two-sided opportunity costs have not so far been discussed in the online auction literature, and our finding sheds light on large-size platform market designs.

5.3 Counterfactual analysis: Bundle-size designs with a resale market

In this subsection, we report the bundle-size counterfactual framework and outcomes for the purpose of regulatory bundle-size policymaking. Throughout this subsection, we consider a benevolent regulator, who solely aims to improve consumer-side welfare, one of the focal points in regulatory policies (see e.g. Train 1991). Thus, the goal of this section is providing a discussion on Pareto improvements among all types of consumers, who demand different degrees of usage. To our knowledge, the bundling literature traditionally focuses on bundles across different types of goods without resale opportunities (e.g. different cable TV channels, operating systems and software, copiers and copier maintenance services, etc.), and the quantity-dimension of bundles with resale opportunities is rarely discussed.[32] Thus, our counterfactual exercise also sheds light on policy discussions on quantity-bundling designs when a frictional competitive resale market exists. As a summary, we find that regulators face challenges to create Pareto improvements among consumers due to the division remainder nature of the demand for bundled goods.[33]

To analyze bundle-size policy designs, we generalize our model with an arbitrary bundle size. In Proposition 5, we derive the individual-level welfare loss equation with the specific case of five-bundled new goods. The proposition can be extended to the case of X-bundled goods, where X is an arbitrary positive integer. The Online Appendix reports this details of this extension.

Proposition 6 - *Individual-level welfare loss with an arbitrary number of bundles*
The individual level utility loss caused by resale market friction costs to a resalable goods user who demands a degree of D usage is

$$WelfareLoss_t(D) = -\frac{X-D}{X}Search_t - \frac{X-D}{X}Resale_t - \frac{D}{X}Scrap, \tag{4}$$

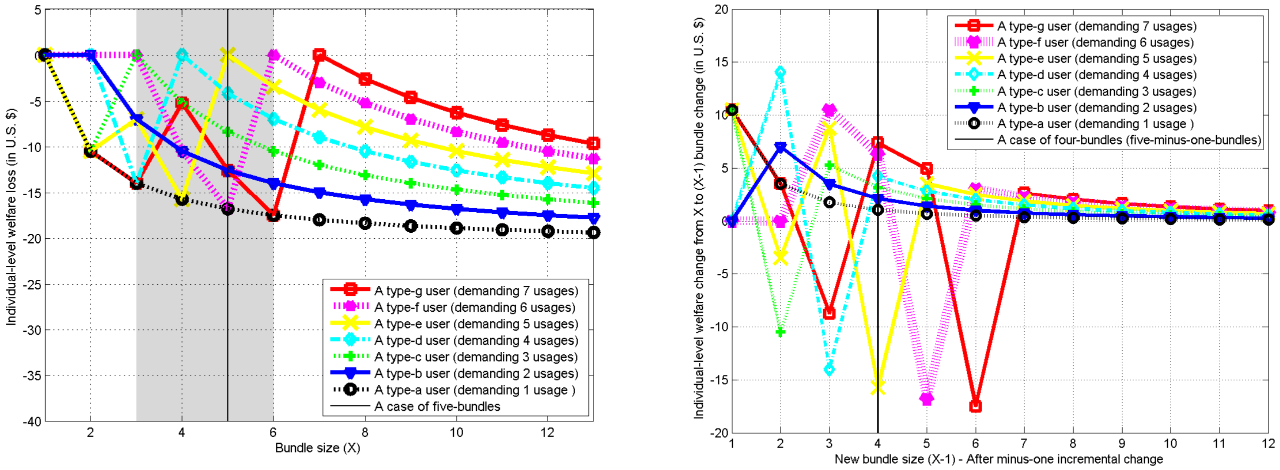
where X is a positive integer bundle size, and $D \in \{a, b, \cdots, X-1, X\}$ is a demanded resalable good usage index.

The above proposition suggests that, if the opportunity costs of $Search_t$, $Resale_t$, and $Scrap$ do not change with respect to X, we can counterfactually simulate the effect of bundle size on the individual-level welfare loss. This counterfactual assumption of constant market frictions could be argued, as a bundle-size design might change the bidder-seller ratio (which we empirically find correlated with friction costs), as well as the arrivals process of sellers and buyers. However, the main finding from this conterfactual exercise is qualitative, not quantitative, which depends not on specific magnitudes but on the existence of resale market friction costs. Specifically, the regulator sets a bundle-size X, and the price of the new good is set by $\overline{P}^{\text{X,New}} = X \cdot \frac{\overline{P}^{\text{V,New}}}{5}$, where $\overline{P}^{\text{V,New}} = \$118.5$, although our individual-level welfare loss discussion is free from a new good price, as manifested in Equation (4). We set the resale market friction opportunity costs as $Search = \$9.69$ and $Resale = \$11.33$, which correspond to

[32] More precisely, quality-dimension bundling is typically categorized into the second-degree price discrimination literature, in which resale trades are traditionally not modeled. As we consider a resale market, this counterfactual exercise also deviates from the second-degree price discrimination literature.

[33] We are grateful to an anonymous referee, who pointed out this model extension to bundle-size designs. As a reference, we also report a numerical calibration model in the Online Appendix, in which we explicitly model arrival processes of sellers and buyers. Specifically, we numerically compare entire-market level welfares between two environments, (a) quantity-bundling (with the bundle-size $X = 5$, 4, and 2) with a resale market and (b) second-degree (two-part tariff) price discrimination without a resale market. Our calibration model in the Online Appendix shows that, compared to a two-part tariff scheme without a resale market, a monopolist could increase its profit by bundling its resalable goods and making them tradable in a resale market. Thus, our numerical analysis provides a rationale for JRs bundling choice. The intuition behind this profit-increasing strategy follows the classical interpretation in the bundling literature: the bundling scheme averages out the diversified willingness-to-pay among different user types, and it enables the monopolist to extract surpluses from low willingness-to-pay consumers. More importantly, our calibration model further reports that, compared to a two-part tariff scheme without a resale market, a bundling scheme with a resale market could generate a Pareto welfare improvement among the monopolist and different types of consumers. See Section 4 of the Online Appendix for details.

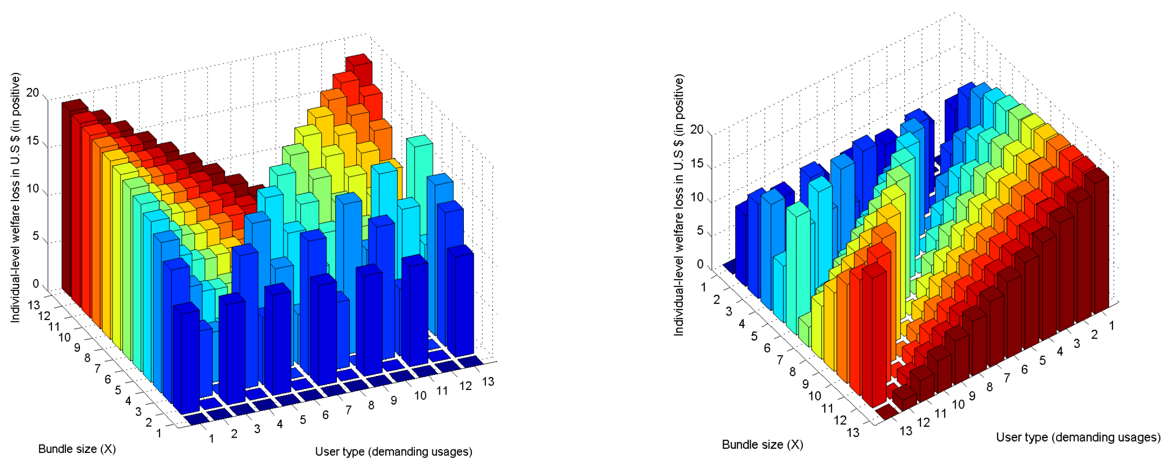
Figure 16: Non-monotone bundle-size effects on individual-level welfare loss: Two-dimensional.



(a) Bundle size and Individual-level welfare loss.

(b) X to $X-1$ bundle change welfare differential.

Figure 17: Non-monotone bundling effects on individual-level welfare loss: Three-dimensional.



(a) Origin view.

(b) Diagonal view.

our main estimation result of Term ③ in Table 3. For this counterfactual analysis, we define $Scrap = \$0$.

By changing the bundle size X, some types of consumers gain, while others lose. Such bundle-design effects are depicted in Figure 16 (a) in the two dimensional form. In the figure, the horizontal axis is the number of bundles that the regulator can design, while the vertical axis is the individual-level welfare loss for each type of users from Equation (4). The solid vertical line expresses the case of $X = 5$, which corresponds our empirically observed bundle size. We consider the welfare loss of a type-g (who demands 7 usages) to a type-a (who demands a single usage) user, expressed by different lines in the figure.

Figure 16 (a) is best explained by an example, in which the regulator gradually changes the bundle size $X = 6$ to $X = 3$. The gray background color in Figure 16 (a) is related to these gradual changes. As an illustration, when the regulator sets $X = 6$, a type-f user (who demands 6 usages) does not incur any resale market friction costs, as she can use up the entire bundle of the new good, and there is no necessity to go to the resale market. However, if the regulator switches the bundle size from $X = 6$ to $X = 5$, she has to purchase a new five-bundled good from the monopolist, as well as an additional used ticket in the resale market to achieve six journeys. Thus, under the design of $X = 5$, a type-f user in the resale market is essentially the same as a type-a user who sacrifices the welfare of $-\frac{4}{5}Search - \frac{4}{5}Resale$. Moreover, if the regulator further changes $X = 5$ to $X = 4$, a type-f user becomes equivalent to a type-b user, who demands the division remainder of 2 usages, incurring $-\frac{2}{4}Search - \frac{2}{4}Resale$. However, somewhat trickily, the welfare loss of this type-f user becomes zero again under a $X = 3$ bundle-size design, as she demands six usages which can be divided by the bundle size of $X = 3$ (i.e. buying two new goods). Accordingly, the bundle design creates largely non-monotone welfare effects among user types, which crucially depend on dividend remainder demands, as illustrated in Figure 16 (a).

These non-monotone effects are further visualized in Figure 17 (a) and (b) in a three-dimensional fashion. In both figures, the first dimension is the type of user, while the second dimension is the regulated bundle-size. The third vertical dimension is the individual-level welfare loss, defined in a positive term. In the figures, under the extreme bundle design of $X = 1$, dis-bundling, no types of users sacrifice his/her welfare, as no user needs to go to the frictional used good market. Also, these three-dimensional figures intuitively report that, as far as ($X >$ demanded usages of a buyer) (i.e. the bundle size is larger than the user's demand), the bundle size effects are monotone. On the other hand, when ($X <$ demanded usages of a buyer) bundle-size effects are non-monotone due to the intrinsic division remainder properties among integer numbers. When ($X =$ demanded usages of a buyer), of course, no welfare loss happens, as the buyers can use up the bundled good.

Lastly, for arguing the possibility of (among consumers) Pareto improvements, Figure 16 (b) depicts minus-one incremental effects of bundle design, considering additional utility gains/losses when the regulator changes the bundle size from X to $X - 1$. In the figure, the horizontal axis shows the after-minus-one-change bundle size (i.e. $X - 1$ bundles), while the vertical axis denotes the incremental welfare gains/losses for each type of buyer caused by an incremental bundle size change from X to $X - 1$. As a illustration, when the regulator changes $X = 5$ to $X = 4$, expressed as a vertical line in the figure, a type-e user (who demands 5 usages) incurs a negative change in the individual-level welfare loss, $-\frac{3}{4}Search - \frac{3}{4}Resale$ (welfare loss for a type-e user under $X = 4$) minus zero (welfare loss for a type-e user under $X = 5$), which is equal to -\$15.765. Contrary, other (type-a, -b, -c, -d, -f, and -g) users have positive welfare gains under this bundle size change.

Figures 16 and 17 indicate that the regulator's bundling design has intricate and non-monotone effects on each type of user, which are crucially dominated by the division remainder demands for of bundled goods. The takeaway regulatory lesson from these counterfactual exercises is clear: a policy maker, who may desire to regulate bundle-size for increasing consumer surplus thorough its bundle-size design, faces challenges to create a Pareto improvement among all types of consumers. The exception is a switch from $X > 1$ to $X = 1$, namely dis-bundling, which all types of consumers weakly prefer. A strong caveat is that, even in such a dis-bundling case, if a regulator further aims to achieve an entire-market Pareto improvement, further caution and investigation are required for a change in monopolist's profit.

6 Conclusion

By proposing a model of a competitive online platform resale market with a no-arbitrage condition, this study deviates from the existing literature by estimating the two-sided transaction costs, rather than a one-sided cost. Specifically, our model provides a salient view of welfare improvement through the existence of a resale market, and it manifests the welfare loss structure caused by buyer-side search and seller-side resale costs in a competitive online resale platform. Our model shows that there are heterogeneous welfare losses among participants, which are particularly disadvantageous to users intending to consume a light degree of goods, forcing some of them to be excluded from trading opportunities. In addition, by using a unique dataset of perfectly substitutable multi-use train tickets, this research empirically reports the large individual-level welfare losses caused by buyer-side search and seller-side resale friction costs. Consequently, this study explicitly manifests a hurdle that curbs the growth of future platform trades, namely non-negligibly large search and resale costs. Technologies for two-sided friction cost reductions are thus a key to accelerating the growth of resalable goods trades.

We end this study by connecting to investigations on such transaction cost reduction technologies, which are actively investigated these days. The roles of search engine mechanisms are studied by Blake et al. (2015) for eBay and Fradkin (2017) for Airbnb transactions. Mobile search technology is investigated by Ghose et al. (2012) for various business services on a Twitter-like platform in South Korea. Ranking mechanisms are studied by Dinerstein et al. (2018) for eBay, and Ursu (2018) for Expedia. Our study uniquely contributes to these emerging literatures by disentangling who the major beneficiaries are of these transaction cost reducing technologies. Our results suggest that they are transient users who demand a small degree of usage.

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