Essays in Industrial Organization and Behavioral Economics

by

Ting-Hao Jordan Ou

A dissertation submitted in partial satisfaction of the requirements for the degree of Doctor of Philosophy in Economics in the Graduate Division of the University of California, Berkeley

Committee in charge:
Professor Stefano DellaVigna, Co-chair
Professor Benjamin Handel, Co-chair
Professor Kei Kawai
Professor Steven Tadelis

Spring 2017
Essays in Industrial Organization and Behavioral Economics

Copyright 2017
by
Ting-Hao Jordan Ou
Abstract

Essays in Industrial Organization and Behavioral Economics

by

Ting-Hao Jordan Ou

Doctor of Philosophy in Economics

University of California, Berkeley

Professor Stefano DellaVigna, Co-chair

Professor Benjamin Handel, Co-chair

This dissertation is comprised of two essays at the intersection of Empirical Industrial Organization and Behavioral Economics. They explore how business decisions are more richly explained with additions in psychological insights commonly found among consumers. These behavioral biases can affect a firm’s decision to participate and their supply in the market, ultimately impacting market competition, supply thickness, and equilibrium.

In Chapter 1, I explore how retailers make entry and exit decisions in the context of an online marketplace. Using a rich panel of internal data from eBay on dedicated sellers, I analyze a feature of the platform requiring sellers to select among monthly contracts that differ in the listing fee schedules. I further exploit a regime change that introduced a monthly allowance of free listings of inventory, altering all contracts from a two-part tariff to a three-part tariff design. This design change was effective in attracting new users and sellers to the platform, encouraging experienced users to become high-volume sellers, and increasing total inventory listed in the marketplace. This is despite little changes in average costs of selling. I demonstrate that standard entry and exit models cannot explain this increase in supply and competition. Instead, I propose loss aversion as an additional factor impacting participation.

Chapter 2 investigates how high-volume, experienced retailers value their products and make supply decisions. Using similar data from eBay and exploiting the same contract feature and policy change, I analyze both the sellers contract choice decisions and the timing of product listings. By estimating a dynamic model of plan choice and listing decisions, I find that sellers have a limited learning period and hold biased beliefs on the option values of their products. Furthermore, they respond heterogeneously to dynamic incentives and future listing costs, leading to an uneven supply of products on the platform. Using the model estimates, I show that debiasing sellers would increase seller surplus by 6% but decrease platform listing revenue by 26%. However, since many platforms generate the majority of revenue from percentage fees on the listings’ values, they may prefer to pursue policies that increase total listings. By targeting specific sellers, such policies can increase aggregate listings on the platform by up to 4.8% at a loss of 5.5% in listing revenue.
Contents

List of Figures  ii

List of Tables  iii

1 Entry and Exit in Online Marketplaces  1
  1.1 Introduction . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 1
  1.2 Setting and Data . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 2
  1.3 Analysis . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 6
  1.4 Discussion . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 10

2 Firm Beliefs and Dynamic Decision-Making: Evidence from the Online Retail Industry  11
  2.1 Setting and Data . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 15
  2.2 Preliminary Analysis . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 18
  2.3 Model and Estimation . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 31
  2.4 Results . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 37
  2.5 Debiasing Sellers . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 45
  2.6 Discussion and Future Work . . . . . . . . . . . . . . . . . . . . . . . . . . . 47

Bibliography  48
# List of Figures

1.1 Total fees charged ................................................................. 5
1.2 Fixed Price Listings .............................................................. 6
1.3 Total Subscribers ................................................................. 7
1.4 Changes in Subscriptions ....................................................... 8
1.5 Listings Among Subscribers .................................................... 8
1.6 New User Accounts ............................................................... 9

2.1 Total fees charged ................................................................. 16
2.2 Plan Switch Fraction by Month ............................................... 19
2.3 Plan Switches and Months on Platform .................................... 19
2.4 Distribution of Monthly Number of Listings ............................... 21
2.5 Monthly Listings ................................................................. 22
2.6 Cumulative Fraction of Listings by Within-Month Period ($T = 5$) . 23
2.7 Within-Month Difference in Listings ....................................... 24
2.8 Suboptimal Plan Choice Patterns ........................................... 28
2.9 Parameter Distribution Estimates from Model .......................... 38
2.10 Parameter Probability Mass Heat Maps ................................... 39
2.11 Parameter Estimates by Months on Platform ............................ 40
2.12 Belief Bias Distribution by Months on Platform ....................... 41
2.13 Parameter Estimates by Months on Platform ............................ 43
# List of Tables

<table>
<thead>
<tr>
<th>Table</th>
<th>Title</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.1</td>
<td>Seller Fee Schedule</td>
<td>4</td>
</tr>
<tr>
<td>2.1</td>
<td>Seller Descriptive Statistics</td>
<td>17</td>
</tr>
<tr>
<td>2.2</td>
<td>Ex Post Loss</td>
<td>30</td>
</tr>
<tr>
<td>2.3</td>
<td>Seller Surplus and Debiasing from Model Estimation</td>
<td>46</td>
</tr>
</tbody>
</table>
Acknowledgments

It is difficult to express my gratitude for the support of everyone that was instrumental in my achievements. Many individuals have influenced my growth and enriched my experiences over the past six years, and I am overwhelmed by the wonderful friendships gained on this journey.

First, I am incredibly lucky to have received the opportunity to work with my advisors at Berkeley. Stefano DellaVigna has guided my academic interests since my first year. From collaborating on research to teaching psychology and economics, he has shown how to tastefully marry economic theory, econometric and statistical analyses, and real-world policy implications. More importantly, Stefano exhibits an attitude and perspective towards work and life that I try to emulate. He has inspired me to be inquisitive and rigorous in my research, to challenge current notions yet be open-minded, and to be intellectually excited about everything I apply myself to. Throughout the years, Stefano has also extended numerous life lessons, often as a result of mistakes I am too embarrassed to mention. Even in the final days of preparing this dissertation, he has provided guidance that is widely applicable to my future professional and personal growth. To claim I aspire to incorporate these traits understates the impact of the wisdoms he has imparted.

Benjamin Handel is the second half of a dynamic duo that sketched my academic and professional blueprints. My conversations with Ben started before arriving at Berkeley, first while visiting graduate programs then, by sheer coincidence, outside my dorm during undergraduate commencement. Since then, Ben has provided an unrivaled level of encouragement in pursuing my research ideas. He has led by example to be bold in my work and to try unconventional methods in answering challenging questions. His course on empirical Industrial Organization examines papers that have pushed the frontier of research. Ben has inspired me to conduct equally influential research, and I can only hope I have met his high expectations.

With Stefano and Ben encouraging me to aim for the sky, Kei Kawai is the mentor that helped build the rocket. He has given me invaluable advice on my research, often taking the time to scrutinize my models and explain complicated research methods in detail. No footnote in my papers was left unturned. I am extremely thankful of the generosity of his time. What started as meetings on research often delved into profound musings on both our professional and personal experiences, and I continue to use these insights to this day.

Finally, Steven Tadelis has been the foundation in my professional development. He has taught me to use unconventional methods, scrutinize institutional details, and envision broad applications in my work. His straightforward words are always appreciated and have constantly reminded me to challenge existing notions. Whether he is in Berkeley, San Jose, Chicago, or Seattle, Steve has always set aside time to meet in person despite his busy schedule. I am extremely thankful for his generosity and time, and I certainly hope to continue our conversations in the future.

Numerous other members of the UC Berkeley community have been helpful during my graduate studies. Many faculty members in the Economics department and Haas School
of Business have been generous with their time. In particular, I would like to thank Ned Augenblick, Aaron Edlin, Joseph Farrell, Shachar Kariv, Jonathan Kolstad, and Ulrike Malmendier for meeting with me and providing guidance. There are also too many classmates to mention with which I have spent late nights and weekends on problem sets, research, and junk food. I will forever cherish these memories and always hope for future encounters. Finally, I would like to thank the support staff in the Economics department, in particular Patrick Allen, Anna Cross, Victoria Lee, and Joe Sibol. Without them, I would have been perpetually lost in the program and may not have finished on time, although I would have relished the chance to stay longer than permitted!

I would like to thank eBay and the Economics team for their generous financial and research support. The opportunity work with a leader in e-Commerce has been a dream come true. In my two summers there, Thomas Blake, Dominic Coey, Dimitriy Masterov, and Kane Sweeney have provided immense support for my research. I am grateful for their guidance as they helped me navigate through the intricacies of this unique industry.

Finally, I would like to thank my parents and brother for their unwavering support during my adventure. They always took the time to express (or at least feign!) interest in my studies, and to remind me of my passion when the going gets tough. They are always there to hear my thoughts and to provide theirs. In their every word and action, it is always to wish me the best.
Chapter 1

Entry and Exit in Online Marketplaces

1.1 Introduction

The rise of the information economy in the past two decades has significantly transformed the retail industry. On the one hand, retailers have access to more sophisticated management tools and face lower barriers to entry, allowing them to reach more customers, expand the number of sales channels, and increase their product offering variety. For consumers, the Internet has displaced the need to visit physical stores for many products and increased the overall ease of price shopping. However, by expanding the retailer’s options, the Internet has also significantly complicated its operations. Decisions such as choosing the optimal sales channel for a particular product (or multiple channels, as “multihoming” products is now a common strategy) and the timing of a product release are potentially both more complex and more likely to be affected by other decisions and factors. For example, channel-specific products such as web exclusivities may increase traffic on one channel, while discounts on goods can impact subsequent demand faced by other channels. As a result, the move towards a more frictionless landscape has raised the importance of both understanding the retailer’s option values and their impacts on the future.

This paper studies a retailer’s decision to enter and exit a marketplace. Using a rich panel of internal data on sellers on eBay, I analyze the timing of their entrances as sellers as a response to fee structure changes introduced by eBay. I exploit a unique feature of the eBay marketplace: all sellers make contract choices at the beginning of each month from a menu of plans, locking in the fee schedules for listing and selling items on the platform for that month. Moreover, eBay changed the fee schedule design in the middle of the time frame, adding a monthly allowance of free listings to each plan and shifting the fee schedules from linear to nonlinear designs. This regime change altered all contracts from a two-part tariff to a three-part tariff and defaulted all sellers onto the new plans. In doing so, the cost of listing now impacts the costs in the future, adding a dynamic component to the seller’s
within-month objective.

The descriptive analysis focuses on the compositions of sellers signing non-default contracts. These subscriptions are aimed at business-to-consumer sellers, rather than the vast majority of sellers on the platform with infrequent inventory. The analysis shows a significant increase in new subscribers after the contract design change, despite overall selling costs to be the same. Moreover, sellers list more products after subscribing, increasing the overall product variety on the platform. Finally, the contract design change succeeded in attracting both existing retailers that added eBay as a new sales channel as well as experienced eBay users looking to start a new business.

Standard models of firm behavior suggest that timing and structure of costs do not impact entry and exit decisions. Rather, the decision is made based on whether economic profits are nonnegative. These models are inadequate in explaining the above results, since competition increased despite overall costs staying the same. This suggests that the fee structure is influential in a firm’s decision to participate. A potential explanation is loss aversion, as the main design change comes from an addition of a monthly allowance of free listings. The inclusion means sellers pay a fee only when the product is sold, so the sellers are less likely to incur negative revenue. This observation is in line with other online platforms, which rely on revenue percentage commissions rather than upfront listing fees.

### 1.2 Setting and Data

The eBay Marketplace platform had 128 million active users (at least one purchase or sale in the calendar year) in 2013. Merchandise can be listed in broad retail categories such as electronics, fashion, and home & garden. They are either sold through one of two primary methods: auction-style listings, in which the item is sold to the highest bidder by a designated deadline; and posted retail prices, where the price is fixed and consumers only decide on quantity. The gross merchandise volume (GMV), the sum of the value of products sold, was $76.5 billion that year, with a net revenue of $8.3 billion for eBay, mostly in seller fees. Approximately 73% of GMV comes from listings with posted retail prices, the method most similarly used by other online retailers and platforms. This is compared to auction-style listings, which had a GMV and listings share of 90% on the platform in 2003 and declined to 50% of GMV and 20% of listings by January 2011 (Einav et al., 2013).

### Selling on eBay

Sellers first register with eBay for a general account, which also allows the sellers to purchase products on the platform. Once registered, the seller is defaulted to the “À la carte” contract plan, which has no monthly upfront fee and is primarily targeted at users with occasional inventory. To choose a plan other than the default, sellers log into their accounts and change the contract separately. While this is an additional step, the process is relatively straightforward and involves few clicks through the web interface to change and confirm. The
contract upfront monthly fee is pro-rated for the first month, and the full amount is charged in the second month. With few exceptions, all users start their monthly billing cycle on the first of the month.

Once a contract is selected, sellers create a listing for each product. Listing characteristics include the pricing style (auction or fixed-price), length of listing (1-day minimum up to indefinite), quantity (single or multi-quantity), and extra listing features (e.g., customized listing descriptions). The seller is asked to confirm the listing and any fees charged before the it is created. Once the listing is created, the seller has limited editing access. Indefinite listings are billed once every thirty days until they are canceled, and most unsold listings are relisted for free unless they are canceled by the seller.

At the end of the month, sellers are billed for all fees incurred during the billing cycle. The main components of the fees include the upfront monthly fixed fee, marginal listing fees, revenue percentage fees (incurred if an item sells), and features fees. The contract fee menus differ primarily on the monthly fixed fee and marginal listing fee, and thus is the main area of focus of the contract plans\textsuperscript{1}. Finally, sellers choose or cancel the contract plan at least one day before the start of next month.

\textbf{Seller Store Contracts}

I consider the set of monthly subscription contracts offered between May 2012 2011 - May 2014, which corresponds to twelve months before and after a contract design change, described in the following paragraph. As mentioned in the earlier section, the focus of the contracts is on the portion of the fee menu relevant to the plan choice and listing behavior. At all points in time, eBay offers four tiers with differing fee menus. From January 2011 - April 2013 (denoted Pre-Period), the contracts feature a two-part tariff design, differentiated by the upfront fixed fee and the marginal listing fee. Plans with a higher upfront fixed fee, which ranges from $15.95 per month on the default plan to $299.95 per month on the highest plan, correspond to lower marginal listings fees, which ranges from 50\textcent per listing on the default plan to 3\textcent per listing on the highest plan.

In March 2013, eBay announced a change in the contract structures, and from May 2013 - May 2014 the contracts switched to a three-part tariff and incorporated a \textit{monthly allowance of free listings} for each plan. Conditional on plan choice, the first number of listings created in the month do not incur a marginal listing fee. After the monthly allowance is used, additional listings incur overage marginal listing fees, which range from 30\textcent on the default plan to 5\textcent on the highest plan. Sellers on the platform prior to the contract change are automatically switched to the corresponding tier.\textsuperscript{2}

\textsuperscript{1}The listing-specific fee menu, such as for additional photos, are identical across plans at a particular time. The revenue percentage fee for fixed-price listings is identical on plans prior to May 2013, and is different for only the default A la carte plan after May 2013. I limit the analysis to sellers who only use fixed-price listings and use counterfactual revenue percentage fees for the one plan that differs, which makes up about 2.4% of the contract choices in the sample.

\textsuperscript{2}Pricing during the Pre-Period also varied by the style of listings. Auction-style listing fees varied
CHAPTER 1. ENTRY AND EXIT IN ONLINE MARKETPLACES

Table 1.1: Seller Fee Schedule

<table>
<thead>
<tr>
<th>Fees</th>
<th>January 2011 - April 2013 (Pre-Period)</th>
<th>May 2013 - July 2014 (Post-Period)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>À la carte</td>
<td>Tier 1</td>
</tr>
<tr>
<td>Fixed upfront fee</td>
<td>$0.00/month</td>
<td>$15.95/month</td>
</tr>
<tr>
<td>Marginal listing fee</td>
<td>50¢</td>
<td>20¢</td>
</tr>
<tr>
<td>Monthly Allowance</td>
<td>None</td>
<td></td>
</tr>
</tbody>
</table>

Notes: Tables present a subset of the seller’s fee menus. Omitted are the percentage fee schedule, optional features fees, marginal listing fees for auction-style listings, and fees for annual contracts. These fees are either identical across plans or not considered by the sample of sellers in the analysis.

Table 1.1 lists the fee menus available in each period. Figure 2.1 illustrates the total fees incurred on the three lowest plans for each period and highlights the fee-minimizing plan for each range of monthly listings.

Data and Sample Composition

I use a rich panel of internal data from eBay, consisting of number of listings at the daily level, aggregate monthly revenue, average listing price, monthly contract choice, and seller demographic information (e.g., start date of accounts). Sellers in the baseline sample satisfy the following conditions: at least three months of activity (strictly positive number of listings depending on the starting price, while the revenue percentage fee varied by contracts. Fixed price revenue percentage fees were equivalent across contracts. Fixed price listing fees also did not vary with price. This dimension of fee variations disappeared with the May 2013 contracts. The paper ignores this distinction in the contracts, as it focuses on sellers who use only fixed-price listings, for reasons explained in the sample composition section.
Figure 1.1: Total fees charged

(a) Pre-Period

(b) Post-Period

Notes: Figures illustrate total listing fees charged for three of the available plans as a function of total number of listings in a month. The fourth plan is omitted to highlight the differences across plans.

or a non-default plan choice); at least 50 listings in seller’s history; and at least 98% of seller’s listings are fixed-price.

The sample represent less than 1% of active sellers in the respective time period on the platform, but more than 20% of all listings and 40% of fixed-pricing listings on the site during this period. I intentionally use a highly selected sample of sellers for external validity and analysis simplification. The restrictions exclude the vast majority of sellers on the platform that only participate occasionally. The constraint to sellers using only fixed-price listings not only provides external validity for retailers outside of eBay that also sell through posted prices, but it also reduces the analysis on plan choice and listing decisions from the significantly more complicated contracts involving auction listings and the starting price. Furthermore, high-volume sellers rely almost solely on fixed-price listings; auction-style listings do not allow for multi-quantity sales, requiring one listing per quantity and thus increasing the time and fees to create more listings. Figure 1.2 illustrates the fraction of listings that are fixed price among sellers who choose contracts versus the all sellers on the platform.

The vast majority of accounts in the sample were started before the data panel and have been active on the platform for an average of four years prior to the panel. The revenue statistics are normalized to the median average monthly revenue in the Pre-Period. Even so, there is significant skew in the revenue and number of listings among the sellers. The vast majority of plan choices are for non-default plans, with 84% of choices in the Pre-Period and 92% in the Post-Period. The mean revenue percentage fee is 8% and 7.9% in the Pre- and Post-Periods, suggesting that this portion of the fees is not significantly different.

---

3Actual listings and revenue as a fraction of the platform’s are not revealed due to disclosure agreement.
1.3 Analysis

This section illustrates descriptive patterns in contract choice. Figure 1.3 demonstrates the changes in number of subscribers on the platform and by contract tier in the twelve months before the contract design change and the twelve months after. Normalized to the total number of subscribers twelve months before the change, the figure shows a relatively low growth in subscribers before the design change, followed by a discontinuous jump after. Most of the growth comes from sellers who previously did not have a contract and choosing Tier 1 as well as sellers previously on Tier 2 upgrading to Tier 3. The total number of subscribers on Tier 2 are similar before and after the design change.

Figure 1.4 further breaks down the contract changes. Both new subscription and upgrade rates increased by approximately 100% compared to the average rates over the 25-month period, whereas the cancellation and downgrade rates declined by 73% and 50%, respectively. Cancellation rates also permanently decreased after the contract change, suggesting sellers are more likely to keep their contracts after the design change.

To see how the contract design impacts the number of listings posted by sellers, I check
CHAPTER 1. ENTRY AND EXIT IN ONLINE MARKETPLACES

Figure 1.3: Total Subscribers

Notes: Figure illustrates the fraction of total listings that are in the fixed price format posted by sellers with subscriptions and by all sellers on the platform.

how they change among new and current subscribers as well as sellers who canceled their contracts. Figure 1.5 illustrates the mean number of monthly listings among new subscribers, current subscribers, and sellers that canceled their contracts. While there is little change in the average number of monthly listings among current subscribers, there is an increase among new subscribers and a decrease among sellers that canceled.

Finally, the contract design attracted both sellers with little experience on the platform, including purchasing items from other eBay sellers, and sellers that have extensive purchase histories on eBay but little selling experience. 1.6(a) illustrates the number of new subscribers that are also new to the platform and created user accounts in the same month. The contract design change increased the total number of new users on the platform. 1.6(b) shows the mean age of user account among new subscribers in each month. The contract design change attracted more early users to the platform. While listing fees changed for all contract tiers, there is significantly change only among sellers signing or canceling subscriptions. Current subscribers do not significantly change the number of listings posted on the platform.
CHAPTER 1. ENTRY AND EXIT IN ONLINE MARKETPLACES

Figure 1.4: Changes in Subscriptions

Notes: Figures illustrate percentage changes in new subscriptions, upgrades, downgrades, and canceled subscriptions relative to the mean of each behavior in the time period. For example, there was 125% more upgrades in the month of the contract design change versus the average number of upgrades in a month over the 25 month period.

Figure 1.5: Listings Among Subscribers

Notes: Figure (a) illustrates the mean number of monthly listings among sellers who are currently on the plan, newly subscribed sellers, and sellers canceling their contracts. Figure (b) demonstrates the mean change in monthly listings among the same three groups of sellers.
CHAPTER 1. ENTRY AND EXIT IN ONLINE MARKETPLACES

Figure 1.6: New User Accounts

Notes: Figure (a) illustrates the total number of user accounts created in a month among new subscribers twelve months before and after the contract design change and in the month of the change. Figure (b) demonstrates the mean age of user accounts among new subscribers in the same time period.
1.4 Discussion

The contract design change’s objectives were to simplify the fee structures, eliminating listing fees based on starting prices and style of listings, and to address various barriers to entry. The new feature significantly increased the number of subscribers, the products listed on the platform, and overall users on the platform.

Despite a listing fee ceiling of 50¢, sellers are nevertheless sensitive to costs incurred before knowing whether the product is sold. The addition of the free allowance of listings and switch from a two-part to three-part tariff design increased the number of new subscribers by eliminating the number of listings subject to the listing fees. Ou (2017b) further suggests the sensitivity to the listing fee, as evidenced by bunching behavior at the listing allowances.

The responses to the design change suggests a larger issue with firms reacting to upfront fixed costs. Case studies have suggested firms hold risk-averse preferences, rather than maximizing just the bottom line. This paper suggests the response is even more extreme, as eliminating small listing fees is significant in increasing the number of new sellers on the platform. Risk aversion by itself is insufficient in explaining this response. Rather, explanations involving disproportional aversion to losses can better explain the behavior.

This observation is in line with responses from other online marketplaces. Competitors of eBay and matching platforms in labor and housing (e.g., Uber and AirBnB) completely eliminated upfront fees and rely only on commissions from sales. This runs counter to standard assumptions on firm entry and exit and suggests the type and timing of costs will also impact a firm’s decision to participate.
Chapter 2

Firm Beliefs and Dynamic Decision-Making: Evidence from the Online Retail Industry

This paper studies the retailer’s process of valuing their products and making intertemporal supply decisions. Using the same, rich panel of internal on high-volume sellers on eBay and exploiting the contract design feature, I analyze the timing of their product listings, which incur fees from the online platform. The setting and contract design have a number of distinct advantages for studying this topic. First, the unique setting allows for comparison of a large number of firms at once (75 thousand in my sample). This is significantly higher than the literature in industrial organization and firm governance, which typically relies on a few large firms in a market or individual case studies. Combined with granular data on seller decisions, I can empirically analyze and back out important characteristics of the sellers. Second, having a history of each seller’s interactions means I can investigate how experience plays a role in learning over time. Third, the change from linear to nonlinear contracts allows for identification of behaviors that would otherwise be unidentified with just one contract design. Finally, the relative simplicity and ease of switching contracts lower the likelihood of such impediments from interacting with the sellers’ decisions. This is in contrast with other menu choice settings such as health insurance and retirement accounts, where both switching and research costs as well as inertia and default biases can significantly impact a consumer’s contract choice (see for example Handel (2013) and Madrian and Shea (2001)).

The analysis begins by presenting a set of stylized facts on plan choices and listing decisions. First, an increase in plan switches around the change from linear to nonlinear fee schedules and the high overall number of switches away from the default plan confirm the relatively effortless changing of plans in this setting. Second, low overall plan switches and persistent levels of monthly listings suggest low degrees of market volatility and uncertainty. Third, evidence of bunching in monthly listings after the introduction of nonlinear schedules imply that sellers respond to the fees. Finally, the trajectory of listings within the month significantly diverged after the contract design change: while sellers list at a uniform rate on
the linear contracts within the month, the change to nonlinear contracts led to a significant portion of sellers decreasing the rate of listings at the beginning of the month and increasing their listings in the last week before the monthly allowance expires. However, this behavior occurs among sellers who never hit the monthly allowance and thus are not subject to any overage listing fees. In contrast, sellers who consistently use close to the allowance actually respond in the opposite manner, listing significantly more in the first week and decreasing their listings in the final week when they use up almost the entire allowance. This has an overall result of making the supply of items less uniform within the month.

The preliminary analysis concludes with a series of ex post efficiency exercises that suggest sellers choose suboptimal plans and do not fully learn from their mistakes. First, 38% of plan choices are suboptimal (20% choose plans meant for more volume and 18% for less), and 86% of those sellers make the same mistake the next month. Moreover, if sellers hypothetically undertook a naive approach to learning and simply used listing behavior in a month to choose next month’s plan, holding next month’s ex post listings constant, the suboptimal choice rate decreases by 76% to less than 10% of all choices. Despite not allowing for sellers to optimize listing behavior conditional on plan choice, this efficiency increase is substantial, as the decrease in money left on the table ranges from $8 by downgrading one plan tier to $7500 by upgrading to the top tier. The mistakes are persistent over time, as sellers are better off even six months later when restricting them to the same plan. Overall, the suboptimal plan choices are quite costly, as the mean loss represents about 5% of a seller’s revenue.

The stylized facts are inconsistent with many of the typical explanations cited in other menu choice settings. First, the evidence and setting rule out common menu costs like switching costs as the main driver of poor plan choice. Second, uncertainty in number of listings and market volatility cannot explain the high persistence in levels of listings and efficiency gain from naive learning. Third, risk aversion cannot explain the dual directions in persistent plan mistakes and would require risk-seeking behavior to explain some of the plan choices. Finally, a homogeneous response to dynamic incentives and future costs of selling cannot explain the diverging trajectories in within-month listings.

Rather than implementing a menu cost or an alternative preference, I consider the influence of a bias in the seller’s decision process. Because high-volume retailers sell through multiple channels, a product’s chosen sales channel is determined by its value on each channel. For example, a phone case may net different profits when sold through eBay or Amazon due to varying customers, fees, and competition, while other products such as produce, due to expiration dates and varying quality, is likely to be less valuable when sold through a website than at a supermarket, where customers can observe the quality and immediately consume. With perfect information on inventory and rational beliefs on the values of the products, sellers can predict the level of listings and choose the correct plan on average. Even with Bayesian updating, one would expect sellers to eventually choose on average the right plan over time. However, this cannot explain the persistence in both suboptimal plan choices and the direction of the mistake in the data. Therefore, I allow for differences between true product values and the ones sellers hold beliefs on. If there is a wedge between the true and perceived product values, a seller may choose a plan meant for a level of volume different
from its true volume, leading to a suboptimal plan choice and listing decisions. Thus, I model this wedge as a bias in the belief of the product values and allow for heterogeneous responses to future costs of selling to explain the evidence.

To quantify the belief bias and response to expected future costs, I introduce a dynamic model of plan choice and listing decisions. Before each month, the seller first chooses a plan based on perceived listing decisions. During the month, a set of products arrive each period, and the seller decides whether to list them on the platform or an outside option (e.g., another platform or physical store). The model characterizes a seller type by two sets of parameters. A set of retail parameters represents the seller size and its product values. Additionally, two behavioral parameters alter the beliefs and preferences of the seller. The first parameter, the belief bias, is similar in approach to Grubb and Osborne (2015) and distorts the perception of the product values, causing the seller to be optimistic or pessimistic about the option value of listing on eBay versus another channel. The second behavioral parameter represents the seller’s heuristic on the option value of listing today, similar to the models in Einav, Finkelstein and Schrimpf (2015) and Dalton, Gowrisankaran and Town (2015). The heuristic captures how the seller weighs the future costs of listing. This matters because they are solving a dynamic problem: if they expect costs to increase later, then they are likely to forgo listing today. Alternatively, if they pay more attention to today’s prices, then their heuristic underweights the future costs.

Both behavioral effects can interact in a dynamic setting. If a seller is optimistic, the distribution of the product values would be perceived to be high and the draws of the values to be low. This would induce a lower rate of listings on the platform at the beginning of the month, and increase near the end of the month before the allowances expire. Alternatively, a seller responsive to future costs can induce a similar listing trajectory. To separately identify the parameters, I first utilize the data from the linear contracts. Because the price to list is a fixed marginal fee, the seller’s day-to-day problem does not depend on the future option value. Of the two behavioral parameters, only the belief bias can influence the seller’s behavior, and does so by causing it to misperceive the values of each contract. Holding the belief bias fixed, the listing decisions on the nonlinear contracts with the monthly allowances would then identify the heuristic parameter.

The empirical framework is similar in approach to the dynamic estimation procedure by Nevo, Turner and Williams (2016) and utilizes techniques from Ackerberg (2009), Bajari, Fox and Ryan (2007), and Fox et al. (2011). The model describes the seller’s problem for a single month, and the estimation procedure matches moments to recover the distribution of seller types for a particular sample. Additionally, by running the procedure on moments indexed by the number of months a seller has been on the platform, I recover the change in the seller type distribution by experience, and can analyze learning from experience and belief updating without imposing additional structure.

The model results show that at least 37% of sellers hold persistently biased beliefs: beliefs do not significantly change after three months, 19% of sellers consistently overestimate the value of their products, and 18% underestimate. A majority of sellers hold nonstandard weights on the future option value: 11% react to current prices more and list earlier in the
CHAPTER 2. FIRM BELIEFS AND DYNAMIC DECISION-MAKING: EVIDENCE FROM THE ONLINE RETAIL INDUSTRY

month, while 44% respond to future incentives more and wait until the end of the month to list their inventories. Moreover, I find higher-volume sellers and experienced sellers to be more likely to be biased, consistent with agency problems and other firm governance issues that may occur in larger firms. Despite these results, I find the distribution of the retailer parameters and retail growth patterns to be consistent with Bar-Gill, Brynjolfsson and Hak (2016), which finds younger business-to-customer (B2C) sellers to grow faster than more mature sellers. More importantly, the product value distribution does not change with experience, reflecting an environment comprised of retailers selling relatively non-differentiated products from a similar set of wholesalers and that the outside options do not significantly change. A model fit confirms the explanatory power of the behavioral parameters: the belief bias rationalizes more types of sellers to choose a particular plan, while both the belief bias and intertemporal weight vary the trajectory of listings during the month and account for within-month variations.

An important consideration is whether to debias consumers through information treatments and reminders. In a counterfactual exercise, I calculate the welfare impact of debiasing sellers on both beliefs and intertemporal heuristics. When debiasing only beliefs, sellers are not substantially better off on average, as most of the gain from lower listing costs are counteracted by a corresponding decrease in revenue (the exception being pessimistic sellers, where an optimal plan choice also means ones with lower listing fees). Debiasing beliefs significantly decreases the platform’s revenues from listing fees by 16% however, coming mostly from optimistic sellers that now choose cheaper plans. Finally, debiasing intertemporal heuristics has an effect on welfare on par with debiasing both beliefs and heuristics. Seller surplus increases by 6.3% on average, while platform revenues from listings decrease by 26.4%. The seller surplus gain comes from a more efficient rationing of the listings allowance and promotes a higher average quality level of products. Not surprisingly, both better rationing of listings and optimal plan choices serve to further lower platform revenue.

Debiasing sellers also have a third effect of impacting supply thickness, and is a point of concern for online platforms. Since the buyer’s value of a platform can be a function of aggregate supply and the majority of a platform’s revenue often comes from percentage fees on the listings’ values, the platform planner may prefer to increase supply at the expense of revenue from listing fees. I show that this is possible with “targeted debiasing,” where only subsets of sellers receive marketing treatments to change their behavior. By treating the subset of sellers that would increase their listings, the platform can increase its supply of items by 4.8% at a loss of 5.5% in listing revenue.

This paper contributes to several distinct literatures. The identification of a seller’s primitives and listing decisions builds on a rich literature investigating a retailer’s intricate operations. First, seminal work on retail costs and market characteristics highlight the determinants and interactions of market entry and competition (e.g., Bresnahan and Reiss (1990, 1991); Basker (2005); Basker and Noel (2009); Aguirregabiria and Suzuki (2014)). This paper adds to these contributions by illustrating the importance of organizational problems such as biased beliefs in decisions along the extensive margin. The emergence of the Internet as a viable environment for commerce has spurned a multitude of research on the behaviors and frictions of this channel: Einav et al. (2013, 2014); Brynjolfsson and Smith (2000) are
examples of literature on this space (see Smith and Zentner (2016) and Tadelis (2016) for surveys). I contribute to this literature by investigating how retailers consider the option values on different sales channels and the impact of biases and heuristics in a platform setting.

The analysis also contributes to a growing research area on firm organization and firm learning. Garicano and Rayo (2016) survey case studies on organizational failures and pose models on perverse incentives and bounded rationality as culprits for internal frictions. This paper provides empirical support to that premise, finding larger sellers to be more susceptible to internal conflicts and that suboptimal decisions can manifest from biased beliefs and heuristics. Second, two recent papers document how firms learn about their setting and operations over time. Doraszelski, Lewis and Pakes (2016) show that firms adapt to market uncertainty and reach equilibrium strategies in the electricity market. Covert (2015) finds that oil companies are reluctant to experiment and ignore data generated from their competitors, over weighting the importance of their own data and capturing just 60% of potential profits from learning. I add to this literature by demonstrating that sellers have a limited learning period, after which beliefs are unlikely to change.

Finally, this paper provides evidence that suboptimal plan choice and the use of heuristics in complex problems also exist in firm settings. A wealth of literature finds evidence of biased beliefs playing a role in plan choices (e.g., DellaVigna and Malmendier (2004, 2006); Grubb (2015)). Perhaps the most closely related literature in this regard is from behavioral finance, where a series of papers suggest boundedly rational CEOs managers can lead to suboptimal firm behavior (see Malmendier and Tate (2015) for a survey). A series of recent papers also demonstrate the use of heuristics. Hossain and Morgan (2006) and Chetty, Looney and Kroft (2009) find inattention of certain aspects of prices among consumers, while Shampanier, Mazar and Ariely (2007) find consumers regard the price of zero completely differently. Inattention is not limited to prices: Lacetera, Pope and Sydnor (2012) find consumers incorporate left-digit bias in their heuristic when shopping for used cars, and Simonsohn (2010) find sellers do not considering their competitors’ actions when timing the ends of auctions. Moreover, Liebman and Zeckhauser (2004); Rees-Jones and Taubinsky (2016); Ito (2014); Brot-Goldberg et al. (2016) suggest consumers do not necessarily respond to the marginal price of consumption. Finally, Einav, Finkelstein and Schrimpf (2015) and Dalton, Gowrisankaran and Town (2015) show that patients are myopic in their drug expenditure, responding dynamically to the nonlinear fee schedule. This paper shows agents can also overreact to dynamic incentives, rather than the underreaction that describes myopic consumers.

### 2.1 Setting and Data

I exploit the same contract decision in Ou (2017a). Sellers first choose a contract at the beginning of each month, which locks in the listing, revenue percentage, and feature fees for the month. At the end of the month, sellers are billed for all fees incurred during the billing cycle.

Table 2.1 provides descriptive statistics for the baseline sample in each period. The vast
majority of accounts in the sample were started before the data panel and have been active on the platform for an average of four years prior to the panel. The revenue statistics are normalized to the median average monthly revenue in the Pre-Period. Even so, there is significant skew in the revenue and number of listings among the sellers. The vast majority of plan choices are for non-default plans, with 84% of choices in the Pre-Period and 92% in the Post-Period. The mean revenue percentage fee is 8% and 7.9% in the Pre- and Post-Periods, suggesting that this portion of the fees is not significantly different.
### Table 2.1: Seller Descriptive Statistics

<table>
<thead>
<tr>
<th>Seller Characteristics</th>
<th>Pre-Period</th>
<th>Post-Period</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of sellers</td>
<td>74,706</td>
<td>72,231</td>
</tr>
<tr>
<td>Mean age of account (years)</td>
<td>8.04</td>
<td>9.05</td>
</tr>
<tr>
<td>Mean age of seller account (years)</td>
<td>4.14</td>
<td>5.12</td>
</tr>
<tr>
<td>Mean average monthly revenue</td>
<td>$3,044.54*</td>
<td>$3,801.34*</td>
</tr>
<tr>
<td>Median average monthly revenue</td>
<td>$1,000.00*</td>
<td>$1,050.75*</td>
</tr>
</tbody>
</table>

**Listings**

| Obs. (daily listings)                      | 51,247,226 | 31,592,041 |
| Mean average monthly listings              | 774        | 926         |
| Median average monthly listings            | 169        | 200         |

**Contract Choice**

| Obs. (seller months)                       | 1,692,967  | 980,343     |
| Months with subscription (%)               | 84%        | 92%         |
| Mean total listing fees                    | $81.86     | $91.82      |
| Mean upfront fee                           | $28.06     | $42.97      |
| Mean listing fees                          | $53.80     | $48.85      |
| Mean final value fee (%)                   | 8%         | 7.9%        |

*Notes: Sample is comprised of active sellers from January 2011 - July 2014 that have at least three months of activity (positive number of listings or active subscription), posted at least 50 listings in their lifetime, and generated at least an average of $500 per month. Sample represents less than 1% of sellers on the platform. All statistics presented in this table refer to the mean statistic by seller. For example, the mean of the per-seller average monthly listings from Jan. 2011 - Apr. 2013 is 774.

* Revenue numbers normalized to the median average monthly revenue in the Pre-Period due to disclosure restrictions. For example, the mean average monthly revenue in the Pre-Period is 3.04 times the median average monthly revenue.
CHAPTER 2. FIRM BELIEFS AND DYNAMIC DECISION-MAKING: EVIDENCE FROM THE ONLINE RETAIL INDUSTRY

2.2 Preliminary Analysis

The analysis begins with three sets of stylized facts on monthly plan choice, aggregate monthly listings, and within-month listing behavior among the sellers. First, I demonstrate that plan choices stay largely the same from month to month, with the majority of switches occurring in the first six months of being on the platform and during the contract regime change. Second, I show that aggregate monthly listings has low volatility and is extremely persistent from month to month, despite evidence that sellers respond to the marginal listing fee. Third, I show that within-month listing trajectories diverge after the regime change to nonlinear contracts and that sellers respond heterogeneously to future costs of listing.

Then, I present a series of ex post optimality exercises that juxtaposes the prior stylized facts and suggest the importance of biased beliefs in this setting. I demonstrate that a substantial fraction of sellers consistently chooses plans that are not fee-minimizing ex post, that the direction of suboptimal choices is persistent, and that simple learning heuristics would eliminate the vast majority of the inefficiencies. The section ends with a discussion on common alternative hypotheses and how they are unlikely to completely explain the evidence presented in the preliminary analysis.

Plan Choice

I describe how sellers choose and switch plans on the platform with three stylized facts. First, the rate of plan switch is fairly low, as between 2-3% of sellers switch plans in most months in my panel. The switch rate increased significantly when eBay redesigned the contracts from a two-part tariff to a three-part tariff (Post-Period), to 4% and 5.5% in the month before and the first month of the Post-Period, respectively. Figure 2.2 illustrates this fact and shows the fraction of sellers that switched plans in the twelve months before and after the contract design change.

Second, the majority of plan switches occur in the first six months of a seller being on the platform. Figure 2.3(a) looks at all sellers in the sample who started selling and have at least 24 months of being on the platform in my panel and graphs the fraction of sellers who switch after a certain number of months of selling experience. About 15% of sellers switch plans in their second month of selling, and that rate converges to about 3-4% after a year of experience.

Third, the plan switches for new sellers are away from the default (À la carte) to a non-default (Tier 1, Tier 2, or Tier 3) plan. Figure 2.3(b) shows the fraction of the same sample in Figure 2.3(a) that have switched to a non-default plan by number of months on the platform. About 28% of sellers start on a non-default plan in their first month, with about 85% on a non-default plan after a year and 95% after two.

I interpret this set of facts as characterizing the ease of changing plans and lack of switching and hassle costs in this setting. Even though the overall rate of plan switches is low, there is a substantial increase in switches when the contract options (and thus their values) changed after the addition of the monthly allowance. Moreover, most of the plan switches
CHAPTER 2. FIRM BELIEFS AND DYNAMIC DECISION-MAKING: EVIDENCE FROM THE ONLINE RETAIL INDUSTRY

Figure 2.2: Plan Switch Fraction by Month

*Notes:* Figure illustrates the fraction of sellers in each month who have a different plan from the previous month. The months are indexed by the number of months before or after the contract change in May 2013.

Figure 2.3: Plan Switches and Months on Platform

(a) Fraction of Sellers Switching

(b) Fraction of Sellers on Non-Default Plan

*Notes:* Figures illustrate the fraction of sellers switching plans (a) and fraction of sellers who have already switched away from the default plan (b) at each month of experience on the platform. Figures use a balanced panel of sellers with at least 24 months on the platform and begin selling after January 2011.
are in the first six months of selling on the platform and away from the non-default plan, suggesting that any potential default effect in plan choice is not likely to exist in this setting. This is consistent with anecdotal evidence on the ease of switching, which is to simply log into the seller’s account, visit a menu specific to the plan choices, and then switch or cancel the plan. There is no need to physically travel to anywhere or call customer service, as is often the case with plan choices in other settings (e.g., cellular service, health insurance, and retirement accounts). Finally, the different plans are relatively straightforward to research, as they differ mostly on three fee components; moreover, eBay offers a calculator to estimate total fees and optimal plan choices. This is in contrast with health insurance and retirement plans, where the relatively high number of contract characteristics significantly increases the complexity of optimal plan choice.

Listing Behavior

This section demonstrates patterns of listings in the sample. I first demonstrate that conditional on plan choice, sellers respond to the marginal listing fee, as evidenced by bunching behavior near the monthly allowance after the plan design switch to nonlinear contracts. Figure 2.4 illustrates the distribution of monthly listings on the Pre-Period linear contracts and the Post-Period nonlinear contracts, normalized to the Post-Period contracts’ monthly allowances (for Pre-Period linear contracts I use the corresponding tier from the Post-Period). The figure shows the relative smoothness in monthly listings in the Pre-Period, whereas there is noticeable bunching at the monthly allowance after the introduction of the nonlinear contracts. The response is noteworthy, considering that listing fees are low relative to other fees and listing prices and range from 30¢ on the default plan to 5¢ on the highest tier. Moreover, the bunching pattern increases on plans with higher marginal overage fees.

Second, there is high correlation and low volatility in the monthly level of listings for a given seller and for all levels of retail volume. Figure 2.5(a) illustrates the correlation for total listings between months: the correlation in listings between month \( m \) and \( m + 1 \) is 0.94, 0.70 between a month and a year later, and 0.56 two years later. Figure 2.5(b) demonstrates the relatively persistent level of listings across all levels of volume. It illustrates a CDF of sellers by its mean monthly listings and a 95% confidence interval of its listings in a two-year period. For example, the average number of monthly listings for the median seller is 250, and 95% of its monthly listings within two years lie between 150 and 375.

The relative lack of uncertainty mean that standard economic theory can explain the bunching response to kinked contracts (e.g., Saez (2010) formalizes this discussion in the context of labor supply). However, nonlinear contracts also provide changing dynamic incentives within the month, as listing any items in a particular period can impact the price of listing in future periods. Einav, Finkelstein and Schrimpf (2015) demonstrates the value of within-cycle data, finding differences in the timings of prescription drug purchases as a result of the nonlinear feature of the healthcare plans. Similarly, Nevo, Turner and Williams (2016) show that consumers respond to the shadow price of consuming broadband, decreasing their usage as they get closer to the broadband cap.
Figure 2.4: Distribution of Monthly Number of Listings

Notes: Figure illustrates the percentage of monthly listing observations as a fraction of the monthly listings allowance on the Post-Period plans. Since there is no allowance on linear plans, the Pre-Period observations are normalized by the corresponding tier’s listings allowance on the Post-Period. The bin width is 0.025, so each point represents the percentage of observations that fall from that fraction of allowance up to 0.025 more than that fraction.
Figure 2.5: Monthly Listings

Notes: Figure (a) illustrates the correlation in monthly number of listings for a seller in month \( m \) and listings up to 24 months later. Figure (b) presents the 10-90 percentile of sellers by their mean number of monthly listings for the first 24 months of observations. The range is the 95% confidence interval.

Similar in concept, I demonstrate that responses to dynamic incentives vary within the month. In the next set of figures, I first divide each month into five periods of roughly six days each to control for weekday dependence and normalize to account for different number of days per month. Figure 2.6 illustrates the distribution of the cumulative fraction of monthly listings (for example, a seller who lists 10% of its monthly listings in period 1 and 20% in period 2 would show up as 10% in period 1 and 30% in period 2; all sellers show up as 1 in period 5) by the end of a period for the linear and nonlinear contracts. The mean (and median) fraction of cumulative listings for periods \( t = 1, 2, 3, 4, 5 \) are \( 0.2, 0.4, 0.6, 0.8, \) and 1, respectively, indicating that the mean seller lists at a uniform rate (he lists one-fifth of listings in each fifth of the month). However, this distribution is noticeably wider on the Post-Period nonlinear contracts: sellers are more likely to deviate from the uniform rate of listings. The nonlinear contracts add an additional dynamic component to the seller’s within-month problem and thus could potentially increase the variation in within-month listings.

Figures 2.7(a) demonstrate that the timing of listings within the month is linked to total monthly listings, and that since monthly listings is persistent, sellers have heterogeneous responses to the dynamic incentives. Sellers who list less than the monthly allowance in a given month, list 3% less than their mean per-period listings in the first period (\( t = 1 \)). In \( t = 3 \), they list roughly the mean rate in \( t = 3 \) and 10% more than the mean in the final period (\( t = 5 \)). By contrast, sellers who end up totaling close to the monthly allowance list 5% more in the first period and 5% less in the final period. Those that list significantly more
tend to list at roughly the mean rate.

Like Einav, Finkelstein and Schrimpf (2015), who find substantial response to the pricing kink close to the end of the cycle, I also find substantial response at the end of the month, and that the behavior is a function of overall listings. However, this behavior is limited only to sellers who consistently list close to the allowance. The higher rate of listings at the beginning of the month is consistent with spotlighting, a phenomenon where agents pay more attention to the current or spot price and less to the future shadow price. More interestingly, sellers who never hit the monthly allowance nevertheless list fewer items on the platform early on in the month, only increasing the rate of listings before the month ends and listing allowance expires. While outside the scope of this paper, this response is consistent with sellers who are averse to paying overages, similar to Shampanier, Mazar and Ariely (2007).

Overall, sellers respond heterogeneously to dynamic incentives, and this is reflected in the timing of the listings. For a substantial fraction of observations that never list more than the monthly allowance, the increase in the rate of listings throughout the month suggests these sellers value future periods more than today, while a smaller fraction of sellers decrease the rate of listings throughout the month.
Figure 2.7: Within-Month Difference in Listings

Notes: Figure illustrates the mean percentage deviation in listings in a period (month is divided into five periods of roughly six days each and normalized by number of days, \( T = 5 \)) relative to the mean listings per period by total monthly listings relative to the plan’s monthly allowance. For example, the average number of listings in \( t = 1 \) for sellers at the allowance \( (x = 1) \) is 5% more than the mean per-period number of listings.

Ex Post Optimal Plan Choice

The preliminary analysis concludes with several exercises on the optimality of plan choices from an ex post perspective. Table 2.2 reports the number of observations by plan choice and the plan that would have minimized the fees conditional on number of listings. The cells along the diagonal are the correct plan choices ex post. In the sample, 38% of plan choices are not fee-minimizing ex post. Sellers oversubscribe, or choose a higher tier plan than the fee-minimizing tier for the number of listings, 20% of the time, while sellers undersubscribe, or choose a lower tier, 18% of the time. The mean amount of loss is $54.99 per month and $706.59 per month at the 1%. In terms of percentage, the mean amount of loss is 4.85% of revenue and 64.6% at the 1%. The loss is asymmetric in the direction of plan choice, as it is bounded by the difference in upfront fees from oversubscribing and unbounded in the undersubscribing direction from the marginal listing fee.

To see whether the suboptimal choice is due simply to uncertainty in number of listings, I conduct an exercise of naive learning and see how much better or worse the sellers do
on average. More specifically, I take the plan that is optimal for a seller in month $m$ and see whether that is the optimal plan for months $m + 1$ to $m + 6$, holding the listings in those months at the actual ex post numbers. This is a conservative estimate of the efficiency
increase, since listing behavior can change conditional on plan choice and net an even greater gain. Table 2.2 details the average and standard deviation of these losses by plan choice, ex post optimal plan, and number of months after.
Whereas 63% of all plan choices are optimal ex post, that rate increases to 91% if sellers choose the plan that was optimal for its behavior one month earlier. As a result, 76% of all suboptimal plan choices can be avoided by simply assuming the this month’s optimal plan and listings for the next month. The optimal plan choice rate decreases overtime, but sellers would still be doing better six months later, as at a rate of 80% it is still significantly better than the sellers’ current choice behavior. The decreases in loss are also substantial, ranging from a 64% average decrease in fees paid for sellers choosing Plan 2 when Plan 3 is ex post optimal in the Pre-Period, to over 98% for sellers choosing the default plan when Plan 2 is ex post optimal in the Post-Period. The loss and efficiencies are bounded by the difference in upfront fixed fee when sellers oversubscribe, but efficiency gains can range from $8 by downgrading from Plan 1 to A la carte in the Pre-Period to $7500 by upgrading from A la carte to Plan 3.

Similar to the optimal plan rate, the efficiency gain also decreases over time, but again sellers would pay fewer fees even six months later.

To see whether the persistent mistakes are in one direction, I check the likelihood of making the same mistake (undersubscribing or oversubscribing) or choosing the optimal plan, conditional on making such a choice (Figure 2.8(a)). About 86% of sellers choose a suboptimal plan one month after choosing the plan, and the direction of the mistake will be the same as well. Sellers continue to make the same mistake months down the line, with 73% continuing to oversubscribe and 66% continuing to undersubscribe six months later. Conversely, sellers who choose optimally are likely to continue to do so, with 82% choosing optimally six months later and 78% one year later. The results are consistent with the earlier evidence on plan choice and monthly listings. Since sellers are unlikely to switch plans after the first few months of selling and monthly listings do not vary from month to month, the persistence in suboptimal plan choice is not surprising.

Finally, experience on the platform does not seem to improve the likelihood of choosing the optimal plan. Figure 2.8(b) illustrates the probability of choosing the optimal plan ex post conditional on months of being on the platform. The rate converges to just over 60% after six months, and actually decreases from the first few months. This decrease comes mostly from sellers switching to non-default plans, meant for higher volumes, faster than they are increasing the number of listings. When sellers do switch plans, the average loss decreases, but the rate of optimal choice is not much higher at 66%.

Discussion and Alternative Hypotheses

The preliminary analysis makes it difficult for standard explanations to explain both poor plan choice and heterogeneous listing decisions. Here I discuss four main alternative hypotheses, some of which were already mentioned in earlier sections.

First, uncertainty in listings and market volatility are unlikely to explain the suboptimal plan choice patterns. The various plans are sufficiently spaced out so that either sellers need large variations in monthly listings, or there needs to be substantially more mass of sellers near the plan cutoffs. Figure 2.5(a), 2.5(b) and 2.4 suggest neither of the two implications...
exist in this setting. Other than the bunching behavior on the Post-Period, which is not near any cutoffs determining plan optimality, there is a smooth distribution of sellers by monthly listings which low variation in listings. The high correlation in total listings from month to month further rules out uncertainty and volatility as the main driver.

Another consideration is switching costs (including hassle and transaction costs), inertia, and default bias. The setting and evidence suggest this also cannot be the main explanation. First, plans are comparatively easy, effortless, and take little time to switch, which requires simply logging into the seller’s account, navigating to the plan menu, and confirming a switch. Moreover, the relative simplicity of the plans and the addition of a fee calculator make the cost of researching alternative plans relatively low, particularly when compared to other settings studied in the literature, where inertia is a substantial concern. Even in the cellular service setting in Grubb and Osborne (2015), which is considerably more opaque and requires more hassle to change, biased beliefs drove the main results. In addition to the setting, the stylized facts do not fully support an explanation involving inertia and default bias, which would imply low switches even during a contract regime changes, a significant portion of sellers still on the default plan, and optimal plans conditional on a switch. Evidence suggests none of these hold: plan switches are three times higher during the contract design change and a majority of sellers switch away from the default plan within three months and 90% within 15. Finally, plan switches are not significantly more likely to be optimal (67% are fee-minimizing ex post). However, they do reduce losses on average (32% lower than mean

Notes: Figure (a) illustrates the fraction of sellers choosing the optimal plan, undersubscribing, or oversubscribing up to twelve months after choosing the optimal plan, undersubscribing, or oversubscribing, respectively. Figure (b) displays the fraction of sellers choosing the optimal plan ex post by months of experience on platform. Both panels are balanced and consist of sellers with at least 24 months of experience and start selling after January 2011.
loss in suboptimal months without plan change), which is a prediction of biased beliefs.

Another potential explanation for not choosing the fee-minimizing plan is risk aversion: averse sellers could choose a plan with higher upfront fees to shield against unexpected increases in listings. However, this cannot possibly explain why some sellers consistently choose plans with lower upfront fees unless I also suppose sellers can be risk-seeking. Moreover, since the number of listings do not change much from month to month (the correlation is 0.94), there is little variation for risk averse preferences to imply different plan choices and would require extremely high coefficients for a constant absolute risk-averse model to rationalize only one side of the suboptimal plan choices.

Finally, homogeneous weights on dynamic incentives cannot explain the varying trajectories in within-month listing behavior. Furthermore, a myopic discount factor like in Einav, Finkelstein and Schrimpf (2015) can explain the slowing down of listings at the end of the month for some sellers, but not the increased rate for others. Instead, I propose a model of biased beliefs and heterogeneous responses to dynamic incentives to explain the evidence. With little change in monthly listings, biased beliefs would explain the persistence in plan choice mistakes. Moreover, it would imply that any plan switches would lower the loss, but not necessarily be the optimal plan, as the threshold could still be further enough away to not switch to the right plan. Heterogeneous responses rationalize different within-month behavioral patterns in a way that a fixed weight on the future option value, such as a discount or myopic factor, cannot.
### CHAPTER 2. FIRM BELIEFS AND DYNAMIC DECISION-MAKING: EVIDENCE FROM THE ONLINE RETAIL INDUSTRY

Table 2.2: Ex Post Loss

<table>
<thead>
<tr>
<th>Plan Choice</th>
<th>Legend</th>
<th>Optimal Plan</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td>Å la carte</td>
<td>Pre-Period (N)</td>
<td>167,470</td>
<td>235,262</td>
</tr>
<tr>
<td></td>
<td>Loss (s.d.)</td>
<td>$0.00 ($0.00)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>With optimal plan</td>
<td>$1.52 ($8.53)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>3 month after</td>
<td>$3.78 ($8.50)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>6 month after</td>
<td>$7.32 ($63.52)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Post-Period (N)</td>
<td>$94.64 ($813.18)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Loss (s.d.)</td>
<td>$2.61 ($11.58)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>With optimal plan</td>
<td>$5.31 ($10.00)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>1 month after</td>
<td>$12.53 ($73.30)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>3 month after</td>
<td>$20.08 ($50.78)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>6 month after</td>
<td>4,457</td>
<td>80,462</td>
</tr>
<tr>
<td></td>
<td>$0.00 ($0.00)</td>
<td>30,689</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$87.61 ($282.10)</td>
<td>4,255</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$111.18 ($701.41)</td>
<td>1,011</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$231,330</td>
<td>345,884</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$340,897</td>
<td>177,571</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$411.18 ($701.41)</td>
<td>1,011</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$683,983</td>
<td>231,330</td>
<td></td>
</tr>
<tr>
<td>Plan 1</td>
<td>Pre-Period (N)</td>
<td>231,330</td>
<td>755,104</td>
</tr>
<tr>
<td></td>
<td>Loss (s.d.)</td>
<td>$8.04 ($4.49)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>With optimal plan</td>
<td>$0.52 ($3.63)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>1 month after</td>
<td>$0.84 ($3.82)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>3 month after</td>
<td>$1.13 ($5.99)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>6 month after</td>
<td>$1.73 ($7.66)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Post-Period (N)</td>
<td>$12.43 ($6.25)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Loss (s.d.)</td>
<td>$12.43 ($6.25)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>With optimal plan</td>
<td>$0.00 ($0.00)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>1 month after</td>
<td>$4.11 ($4.63)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>3 month after</td>
<td>$4.08 ($12.21)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>6 month after</td>
<td>$5.29 ($13.50)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$231,330</td>
<td>345,884</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$177,571</td>
<td>1,011</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$469,353</td>
<td>231,330</td>
<td></td>
</tr>
<tr>
<td>Plan 2</td>
<td>Pre-Period (N)</td>
<td>28,303</td>
<td>683,983</td>
</tr>
<tr>
<td></td>
<td>Loss (s.d.)</td>
<td>$38.12 ($7.11)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>With optimal plan</td>
<td>$2.04 ($9.17)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>1 month after</td>
<td>$2.98 ($8.09)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>6 month after</td>
<td>$4.22 ($9.90)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Post-Period (N)</td>
<td>$5.26 ($4.63)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Loss (s.d.)</td>
<td>$5.26 ($4.63)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>With optimal plan</td>
<td>$0.00 ($0.00)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>1 month after</td>
<td>$3.19 ($4.57)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>3 month after</td>
<td>$11.13 ($91.44)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>6 month after</td>
<td>$22.05 ($142.97)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$28,303</td>
<td>91,401</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$560,897</td>
<td>4,255</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$4,234</td>
<td>220,053</td>
<td></td>
</tr>
<tr>
<td></td>
<td>3,382</td>
<td>683,983</td>
<td></td>
</tr>
<tr>
<td>Plan 3</td>
<td>Pre-Period (N)</td>
<td>318</td>
<td>62,926</td>
</tr>
<tr>
<td></td>
<td>Loss (s.d.)</td>
<td>$291.05 ($7.48)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>With optimal plan</td>
<td>$20.47 ($66.97)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>1 month after</td>
<td>$2.16 ($12.07)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>6 month after</td>
<td>$37.04 ($85.94)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Post-Period (N)</td>
<td>$318.93 ($66.97)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Loss (s.d.)</td>
<td>$318.93 ($66.97)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>With optimal plan</td>
<td>$0.00 ($0.00)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>1 month after</td>
<td>$5.58 ($81.31)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>3 month after</td>
<td>$94.79 ($91.60)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>6 month after</td>
<td>$93.94 ($86.83)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$318</td>
<td>91,401</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$8,728</td>
<td>4,255</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$62,926</td>
<td>318</td>
<td></td>
</tr>
</tbody>
</table>

**Notes:** Table displays the number of plan choices by the fee-minimizing choice holding the listings at the actual ex post number, the average and standard deviation of loss, and the loss for one, three, and six months after switching and fixing the optimal plan. For example, the cells along the diagonal are plan choices that are ex post optimal. Hence, the average loss in these cells are $0.
2.3 Model and Estimation

The analysis in the previous section provides evidence suggesting that sellers optimize in a way that deviates from a standard firm profit-maximization model. This section presents a dynamic model of plan choice and listing decisions motivated by the preceding descriptive results and the setting. The model is meant to illustrate a retailer participating not just on the eBay platform, but also potentially on other platforms (e.g., Amazon, Etsy) or in other channels (e.g., brick-and-mortar stores). Given the potential to participate on other markets and the relatively diminutive size of the contract’s fees to a retailer’s other costs, I assume the seller primitives are independent from the contract choice. In the empirical procedure, I employ a method-of-moments approach that estimates the distributions of seller types and primitives in the sample. The procedure also allows for an analysis on learning without additional functional forms.

The timing of the model builds on the framework used in the contract choice and usage model in Nevo, Turner and Williams (2016). To model biased beliefs, I add a wedge between the perceived and true distribution of the taste shocks, similar to Grubb and Osborne (2015). To model intertemporal weights, I follow the approach in Einav, Finkelstein and Schrimpf (2015) involving myopia, but allowing for the possibility of greater weights on the future.

This section covers the model of the seller’s problem, identification, estimation procedure, and description of the data samples. I conclude with a discussion on modeling decisions.

Model

I consider a risk-neutral, forward-looking seller who faces stochastic product value shocks. The seller’s problem is modeled in two stages. The seller first chooses a plan anticipating future listing behavior, and then chooses usage given the chosen plan.

Let a seller of type $h$ be characterized by the vector of parameter values $(\lambda_h, \mu_h, \sigma_h, \gamma_h, \rho_h)$. $\lambda_h$ is the fixed number of products that arrive every period for the seller to consider listing on eBay, sold through another channel, or discarded. $\mu_h$ and $\sigma_h$ describe the distribution of the option values of the products, where a positive product value means the item would net more revenue than the seller’s second best option. $\gamma_h$ is a biased belief parameter that distorts the seller’s perception of the value distribution, and $\rho_h$ is an intertemporal weight that captures heuristic on the option value of listing today. Sellers choose a plan $k$ at $t = 0$, where plan $k$ is characterized by an upfront fixed fee $F_k$, listing allowance $T_k$, and overage price $p_k$. In every period $t = 1, ..., T$, the seller chooses a number of items $\ell_t$ to list. The cumulative past listings $L_t = L_{t-1} + \ell_t$ is the only state variable for the model and starts at zero at the beginning of the month ($L_0 = 0$). For notational purposes, I drop $h$ and $k$ in the following equations.

Conditional on contract choice $k$ and cumulative listings $L_{t-1}$, $\lambda_h$ items arrive for the seller to consider listing at the start of each period $t = 1, ..., T$. The values of the product draws, characterized by the vector $v_t = \{v_1^t, v_2^t, ..., v_{\lambda_h}^t\}$, are independent and identically distributed: $v_i^t \sim N(\mu_h + \eta_t, \sigma_h^2)$, where $i = \{1, 2, ..., \lambda_h\}$ and $\eta_t$ is a platform-wide demand
CHAPTER 2. FIRM BELIEFS AND DYNAMIC DECISION-MAKING: EVIDENCE FROM THE ONLINE RETAIL INDUSTRY

shock in time $t$. The seller perceives the values to be distributed $v^i_t \sim N(\gamma_k\mu_k + \eta_t, \sigma_k^2)$. Note that the seller perfectly perceives the demand shock and is not meant to be an error. This modeling decision reflects the predictable trends in browsing behaviors within the month.

After the product value draws, the seller chooses $\ell_t$ to optimize its value function:

$$V_t(v_t, L_{t-1}) = \max_{\ell_t \leq \lambda_t} \sum_{i=1}^{\ell_t} v^{(i)}_t(v_t) - p_k \cdot \max\{L_{t-1} + \ell_t - \bar{L}_k, 0\} + E[V_{t+1}(L_{t-1} + \ell_t)],$$

where $v^{(i)}_t(v_t)$ is the $i$-th highest value in $v_t$ and $p_k$ is the marginal overage fee in for the chosen contract. The revenue at time $t$, $R(v_t, \ell_t)$, is a function of the product value draws $v_t$ and number of listings $\ell_t$ and is the sum of the top $\ell_t$ values in $v_t$. The overage function $O_k(L_{t-1}, \ell_t)$ returns the number of listings that are over the monthly limit $T_k$ on which the seller must pay overage fees. The leftover $\lambda_t - \ell_t$ items are either sold on an outside platform or discarded, and receive a value of 0. At the end of each period, the cumulative listings state variable is updated: $L_t = L_{t-1} + \ell_t$.

The timing and structure of the model are chosen to specifically reflect the decision problem of a typical seller in this space while still retaining tractability. A fixed arrival number of products captures the size of the seller in any given month, while the value distribution captures the notion of multiple sales channel options. Treating the values as stochastic shocks reflect the uncertainty in demand for the sellers’ product on not just eBay, but on competing platforms and in other sales channels as well.

Optimal Listing Behavior

I now solve for the optimal listing behavior implied by the above model. Since the billing cycle ends after $T$ periods, the model is solved recursively, starting with period $T$.

In the terminal period $T$, the seller solves a static profit-maximization problem, as there is no intertemporal tradeoff. Given past cumulative listings $L_{T-1}$ and draw of values $v_T$, the seller starts with the highest-valued product and lists down the products until either the overage price is higher than the next product value, the next product value is negative, or there are no more products left. Denoting the optimal listing behavior by $\ell^*_T(v_T, L_{T-1})$, the seller’s profit in the terminal period is

$$V_T(v_T, L_{T-1}) = R(v_T, \ell^*_T(v_T, L_{T-1})) - p_k \cdot O_k(L_{T-1}, \ell^*_T(v_T, L_{T-1})).$$

For any other period $t < T$, the seller optimizes the value function, and the policy function incorporates the change in a period’s state from listings in the past period. The seller thus solves

$$\ell^*_t(v_t, L_{t-1}) = \arg \max_{\ell_t} R(v_t, \ell_t) - p_k \cdot O_k(L_{t-1}, \ell_t) + E[V_{t+1}(L_{t-1} + \ell_t)].$$

Following Nevo, Turner and Williams (2016), I define the shadow price of listing $\hat{p}$:
\[
\tilde{p}_k(L_{t-1}, \ell_t) = \begin{cases} 
p_k, & \text{if } O_k(\ell_t, L_{t-1}) > 0, \\
\rho_h \cdot \frac{\Delta E[V_{t+1}(L_{t-1} + \ell_t)]}{\Delta \ell_t}, & \text{if } O_k(\ell_t, L_{t-1}) = 0.
\end{cases}
\]

The intertemporal weight \( \rho_h \geq 0 \) affects the seller’s perception of the shadow price of listing. A seller with \( \rho_h = 1 \) responds to any variation in the shadow price as the true variation. A seller with \( \rho_h < 1 \) responds more to the current period’s price, or spot price, than to changes in the shadow price, while a seller with \( \rho_h > 1 \) overweights the future price of listing. For linear contracts where \( L_k = 0 \), the shadow price of listing is always equal to the marginal listing fee: \( \tilde{p}_k(L_{t-1}, \ell_t) = p_k \forall \ell_t \geq 0, L_{t-1} \geq 0. \)

The optimal listing behavior is then

\[
\max_{\ell_t \leq \lambda_h} \ell_t^*: v(\ell_t^*)(v_t) \geq \tilde{p}_k(v_t, L_{t-1}, \ell_t^*),
\]

Intuitively, since the revenue of listing \( \ell_t \) items is the sum of the highest \( \ell_t \) values in \( v_t \), the marginal revenue of listing, \( MR(v_t, \ell_t) \), is the value of the \( \ell_t \)-th item. Similarly, the marginal cost of listing, \( MC(v_t, L_{t-1}, \ell_t) \), is the shadow price of listing. Thus, the seller chooses to list all items with values greater than the shadow price:

\[
v^* \in v_t: v \geq \tilde{p}_k(L_{t-1}, \ell_t^*).
\]

Given the optimal listing behavior, the expected value function for type \( t \) on contract \( k \) is

\[
E[V_t(L_{t-1})] = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \ldots \int_{-\infty}^{\infty} V_t(v_t, L_{t-1}) dv_t^1 dv_t^2 \ldots dv_t^\lambda_h
\]

and the expected listing behavior at each state is

\[
E[\ell_t^*(L_{t-1})] = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \ldots \int_{-\infty}^{\infty} \ell_t^*(v_t, L_{t-1}) dv_t^1 dv_t^2 \ldots dv_t^\lambda_h.
\]

Note that on linear contracts with no allowances (\( L_k = 0 \)), the shadow price of listing does not depend on cumulative past listings. Therefore, the shadow price is always equal to the marginal listing fee (\( \tilde{p} = p_k \)), and the Bellman equation simplifies to a static problem that is independent of the period.

**Plan Choice**

A seller of type \( h \) anticipates future usage and expected value of each plan, calculated recursively through the process in the earlier section. Thus, the plan choice is given by

\[
k^*_h = \arg \max_{k \in \{0,1,\ldots,K\}} \left\{ E[V_{hk1}(0) - F_k] \right\},
\]

where \( K \) is the number of available plans and \( F_k \) the upfront fixed fee.
CHAPTER 2. FIRM BELIEFS AND DYNAMIC DECISION-MAKING: EVIDENCE FROM THE ONLINE RETAIL INDUSTRY

Identification

Our primary identification challenge is identification of the belief bias $\gamma_h$ and the intertemporal weight heuristic $\rho_h$. The two parameters are unidentified when using just the Post-Period nonlinear contracts. As an example, both a seller overestimating its mean product values, $\gamma_h > 1$, and another overweighting the future option value, $\rho_h > 1$, can generate the same upwards trajectory in listing behavior within the month. Rather, my identification strategy will rely on estimating all but one parameter ($\rho_h$) and time shock $\eta_t$ on the Pre-Period linear contracts, and then fixing the type distribution and estimating $\rho_h$ on the Post-Period nonlinear contracts.

The linear fee schedules in the Pre-Period imply that the shadow price of listing is fixed ($\tilde{p}_k(L_{t-1}, \ell_t) = p_k$), the seller’s problem is identical across periods conditional on plan choice $k$. Thus, variation in the listing behavior from period to period reflects the draws in those periods, which allows me to identify the retail parameters $\lambda_h, \mu_h$, and $\sigma_h$. The listing behavior and market-wide time shock identifies the retail parameters $\lambda_h, \mu_h, \sigma_h$. First, the mean listings and market shocks identify $\lambda_h$ and $\mu_h$. Additionally, variation in usage and therefore the likelihood of reaching each state identifies $\sigma_h$. As the number of listings in a period is determined purely on the draw of product values for that period and does not factor the future option value in the first-order condition, $\gamma_h$ is not identified from the listing behavior. Rather, $\gamma_h$ is identified from the contract choice. Finally, the sum of listings across sellers in a period identifies $\eta_t$, as the model predicts uniform mean listing behavior across all periods. Note that the intertemporal weight parameter, $\rho_h$, cannot be identified here as the overage function is automatically positive: $O(L_{t-1}, \ell_t) > 0$.

Given $\lambda_h, \mu_h, \sigma_h$, and $\gamma_h$, the Post-Period listing behavior identifies $\rho_h$. Practically speaking, I assume stationarity of types between the two periods and constrain the distributions of $\lambda_h, \mu_h, \sigma_h$, and $\gamma_h$ to the ones estimated from the Pre-Period. The parameters cannot be separately identified on just the Post-Period sample. I conduct robustness checks for the stationarity assumption by estimating the type distributions on monthly samples and find that the estimated distributions do not deviate in a statistically significant manner. Finally, I note that while the functional form of the market shock $\eta_t$ drives the identification of $\lambda_h$ and $\mu_h$, the interpretations and counterfactuals rely on the multiplicative nature of the two parameters, and thus the form is assumed for practical purposes to generate a unique pair of parameter values.

Estimation

The procedure estimates the distribution of seller types in a given data sample, from which I can then recover the distribution of parameters. I use a method-of-moments approach similar to the algorithms developed and used by Nevo, Turner and Williams (2016); Fox et al. (2011); Bajari, Fox and Ryan (2007); Ackerberg (2009). First, I select the data samples for which I am interested in recovering the distribution types for and calculate their respective empirical moments. Next, I solve the dynamic program for the two sets of plans on a wide
variety of seller types. Last, I estimate a weight for each of the types by matching the
moments from the weighted optimal behavior from the simulations, calculated in the second
step, to the equivalent moments observed in the data. I interpret the estimated weights as
the distribution of seller types. In this section I outline the main steps of the procedure, and
provide more details and robustness checks in the Online Appendix.

In the first step, I choose the following two sets of moments, motivated by computational
ease and identification. First, I choose the weighted mean listing behavior for type
$h$ on plan $k$ in time $t$ at each state $L_{t-1}$:

$$
\sum_{h=1}^{H} E[\ell^*_{hkt}(L_{t-1})] \times \varphi_{hkt}(L_{t-1}) \theta_h,
$$

where $E[\ell^*_{hkt}(L_{t-1})]$ is the mean listings, $\varphi_{hkt}(L_{t-1})$ is the probability that this type reaches the state, and $\theta_h$ the
weight to be estimated in Step 3. Since the average is taken across all types on plan $k$, the
moment will be linear in the parameters. The second set of moments is the mass of sellers at
a particular state, $\sum_{h=1}^{H} \varphi_{hkt}(L_{t-1}) \theta_h$, which is also linear in the weights. These moments
also satisfy the identification requirements mentioned earlier.

In the second step of the estimation, I solve the dynamic program for 14,474 seller types,
where each type is defined by the parameter vector $(\lambda_h, \mu_h, \sigma_h, \gamma_h, \rho_h)$. The five parameters
have various points of support, with all except one chosen uniformly within a range (support
for $\lambda_h$ is chosen exponentially to follow the skew in listings). The state space is discretized to
nonnegative integers since cumulative past listings are integer values. For a seller of type
$h$, I solve the finite-horizon dynamic program described in the previous section recursively,
starting in period $T$. This determines the expected surplus and policy function given plan
choice $k$. I solve a separate dynamic program for the same seller type in accordance with the
behavioral parameters $(\gamma_h, \rho_h)$ to generate the perceived surpluses and policy functions for
each plan. I use the simulated policy functions from the first dynamic program and the plan
choices from the second dynamic program in my matching procedure.

In the third step of the procedure, I choose a weight for each seller type to match the
moments from the data to the weighted average of the behavior predicted by the model.
Formally, I choose weights to satisfy

$$
\hat{\theta} = \arg \min_{\theta} \mathbf{m}_k \hat{V}^{-1} \mathbf{m}_k(\theta)
$$

subject to $\sum_{h=1}^{H} \theta_h = 1$ and $\theta_h \geq 0 \forall h$.

The plan-specific vector $\mathbf{m}_k(\theta)$ is defined as $\mathbf{m}_k(\theta) = \hat{\mathbf{m}}^\text{data}_k - \mathbf{m}^\text{model}_k \cdot \theta$, where $\hat{\mathbf{m}}^\text{data}_k$ is the
vector of moments recovered from the data, $\mathbf{m}^\text{model}_k \cdot \theta$ is the weighted average of the equivalent
simulated moments predicted by the model, and $\hat{V}^{-1}$ is a weighting matrix. The weights
are constrained to be non-negative and sum to 1 for each plan so they can be interpreted as
probabilities. Finally, the weights are normalized by the probability that each plan is chosen,
and therefore I also match the share of each plan in the data. Since the moments are linear
in the weights, I use constrained least squares minimization to choose the estimates (Bajari,
Fox and Ryan (2007)).

The standard errors are calculated using a block-resampling methodology (Lahiri (2003)).
I sample the data by seller with replacement, keeping all periods for each seller drawn. For
each sample, I recalculate the moments and then re-estimate the weights. I calculate standard errors for subsequent statistics and counterfactual analyses by repeating the calculation using the 1,000 different estimates of the weights.

The estimate procedure chooses the combination of weights for each seller type that best matches the data. I first use the subset of seller types implied by the dynamic program that would choose each plan. Next, I match the empirical moments on the weighted simulated moments to recover the weights. Since the estimation process uses constrained least squares minimization, the weights are identified as long as the behavior among types are not collinear over all moments and states.

**Data Samples**

The method-of-moments approach recovers the distribution of seller types for a particular data sample. By using different samples, estimating the weights, and then analyzing the distributions, I can uncover additional insights about the sellers without imposing additional structure.

To describe the general sample of sellers, I aggregate all observations in the Pre-Period and Post-Period. Implicit in this aggregation is an assumption of stationarity of seller types across months, since I combine multiple observations from the same sellers. Thus, I further break down the observations by month and quarter (three months) to test this assumption. Finally, I generate 1,000 samples of data by block-sampling sellers. This set of data samples is used for standard errors.

The next set of data samples is used to analyze learning and changes in the parameter distribution over time. For each seller, I re-index their observations to the number of months they have been on the platform. Then, I aggregate the observations by each experience-month index. Therefore, the estimated weights for each data sample uncovers the type distributions at each experience-month index, which allows me to observe changes in the parameter distributions with seller experience and learning.

**Discussion**

The model describes the dynamics only within one month because the focus is on the belief bias and intertemporal weights, both of which can be estimated using monthly plan choice and within-month listing decisions. Each parameter and its dynamics is motivated by the stylized facts in the preliminary analysis. The retailer parameters, $\lambda_h, \mu_h, \sigma_h$, establishes a “baseline” fixed listing behavior within the month. The belief bias $\gamma_h$ changes behavior in two ways, first by rationalizing plan choices that are not ex post fee-minimizing, and second by adding trajectory in listing behavior within the month. However, a belief bias that rationalizes a plan choice in one direction (e.g., $\gamma_h > 1$ implies choosing a higher tier plan than the fee-minimizing one) also implies a particular trajectory ($\gamma_h > 1$ generates an increasing trajectory with lower rates of listings at the beginning of the month). Because
CHAPTER 2. FIRM BELIEFS AND DYNAMIC DECISION-MAKING: EVIDENCE FROM THE ONLINE RETAIL INDUSTRY

the data suggests there are also sellers who oversubscribe on plans and have a decreasing trajectory, I introduce $\rho_h$ to account for other observed behavior.

There are two additional assumptions I implicitly make that is worth addressing. First, I assume the parameter values governing the seller type is not influenced by the plan choice and listing behaviors. Second, I assume sellers are sophisticated about the intertemporal weight. That is, the seller is aware that future decisions take this weight into consideration. Since I interpret the weight as a heuristic for calculating the future option value, this is consistent with the seller being cognizant of the weight.

Examples of simulated behavior for different seller types further illustrate the effects of the parameters and are in the Online Appendix, along with further details on the algorithms and computational challenges.

2.4 Results

I estimate a weight greater than 0.1% for 115 types of sellers, with the top ten types accounting for 34% of the population. The average product arrival number ($\lambda_h$) is 181 items per period, and the average mean of the product value distribution ($\mu_h$) is 0.23. 19% of the population are optimistic about the value of their products ($\gamma_h > 1$) and perceive the mean of the distribution to be greater than the true mean. 18% are pessimistic ($\gamma_h < 1$) and underestimate the mean of the distribution. 11% of sellers are more responsive to the spot price ($\rho_h < 1$) and list more items at the beginning of the month, while 44% weigh the future option value ($\rho_h > 1$) more and wait until later in the month. Figure 2.9 show the distributions of $\lambda_h$, $\mu_h$, $\gamma_h$, and $\rho_h$. Overall, 39% of sellers hold standard beliefs and exhibit standard dynamic response ($\gamma_h = 1$, $\rho_h = 1$).

The estimated distributions on the retailer parameters $\lambda_h$ and $\mu_h$ seem reasonable for the setting and sample. The average product arrival number $\lambda_h$ of 181 items per period corresponds to 36 items per day and 1080 items per month, which is consistent with the data as the sample is narrowed to only the highest-volume sellers on the platform (recall the mean number of monthly listings is 926 in the Post-Period). Similarly, the vast majority of sellers have a product value distribution with a mean less than 40¢. Since $v_t$ is interpreted as the added value of listing on eBay versus the second-best option (e.g., listing on a competitor platform or discarding) and the vast majority of merchandise are in categories that other platforms also participate in and have near-perfect substitutes, it is not surprising that the value distributions are skewed towards zero. Finally, a nontrivial percentage of the sellers have a negative mean for the value distribution mean. This is consistent with the portion of retailers such as Best Buy, Target, and Adorama that mostly sell through their own or other channels but will still list on eBay.

The estimated distributions on the belief bias $\gamma_h$ and dynamic incentive weight $\rho_h$ are consistent with our preliminary analysis on plan choice and listing behavior. That the belief bias is symmetric in directions is reflected in the plan choices being ex post suboptimal for a set of consistently undersubscribing sellers and a set of consistently oversubscribing sellers.
The 11% underweighting dynamic incentives corresponds with the sellers shifting their listings to earlier in the month after the change to nonlinear contracts. The lower weight puts more emphasis on the “spot price,” or the marginal price the seller encounters today. Conversely, the 44% found to overweight dynamic incentives shifts the listings to a later point in the month in the Post-Period.

Figure 2.10 presents heat maps between different parameters to illustrate the probability mass of seller types in each bin. In comparing the intertemporal weight $\rho_h$ and product arrival number $\lambda_h$, I find even large sellers to hold nonstandard dynamic responses. I also find that having nonstandard behavior along one dimension (belief or dynamic incentives) is correlated with having nonstandard behavior along the other. That the bias is more prevalent among
CHAPTER 2. FIRM BELIEFS AND DYNAMIC DECISION-MAKING: EVIDENCE FROM THE ONLINE RETAIL INDUSTRY

larger sellers is consistent with an organizational failure story, where the added complexity of a larger organization may cause the decision-maker to use heuristics and generate more wedges.

The computed standard errors are relatively small, as it is driven by the aggregate moments used in the estimation procedure. Most of the variance in listing behavior come from day-of-week dependence, as individual sellers may have different, but persistent, listing patterns from week to week. At the aggregated level (total of five $T = 5$), seller behavior is persistent from month to month. Similar to findings in Nevo, Turner and Williams (2016), the lack of variance at this level of listing behavior mean there is little imprecision in the estimates.

Figure 2.10: Parameter Probability Mass Heat Maps

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{parameter_heatmap.png}
\caption{Parameter Probability Mass Heat Maps}
\end{figure}

\begin{itemize}
\item \textbf{(a) $\log(\lambda_h)$ vs. $\rho_h$}
\item \textbf{(b) $\log_2(\gamma_h)$ vs. $\rho_h$}
\end{itemize}

\textit{Notes:} Figures illustrate the estimated probability mass for each discretized bin.

Experience, Learning, and Persistent Beliefs

Results show that sellers grow over time in a manner consistent with the selected sample and setting. Figure 2.11(a) illustrate the change in the mean product arrival number $\lambda_h$ for sellers with at least one year of experience from their first month on the platform to one year later. I find an average product arrival number of 11 items per day (65 items per 6-day period) in the first month of selling on the platform, and this number grows to 18 items per day (110 items per 6-day period) by the end of their first year. This is consistent with Bar-Gill, Brynjolfsson and Hak (2016), who also find younger and smaller sellers to experience the fastest rates of growth. Figure 2.11(b) shows the average mean of the inventory value distribution by experience-month. The relative lack of change in the inventory value and the
growth pattern in seller inventory size are consistent with a setting in which online retailers sell relatively homogeneous goods and have outside marketplaces to list their merchandise.

Despite evidence of sellers growing in a manner consistent with the setting, I find that beliefs do not significant change after six months of being on the platform. Figure 2.12 illustrates the population distribution of belief bias by months on the platform. The estimated distribution is consistent with the preliminary evidence on ex post plan choice behavior. Similar to how sellers are more likely to be on the optimal plan in the first six months, the model predicts sellers to hold rational beliefs with a higher likelihood in the same time frame. Likewise, the distribution on intertemporal heuristics does not significantly change with months on the platform (see Online Appendix).

Figure 2.11: Parameter Estimates by Months on Platform

(a) $\lambda_h$

(b) $\mu_h$

Notes: Figures illustrate the mean of the parameter estimates from the main specification by months of experience on the platform. Each point represents a separate estimation on a data sample consisting of moments re-indexed by experience.

Overall, the evidence and model suggest there is a limited period of learning, where sellers increase in size and update their beliefs in the first months of experience. However, as the sellers become larger over time, the beliefs and heuristics become persistent, and the resulting biases lead to suboptimal plan choices and uneven listing rates within the month.

**Robustness Checks and Model Fit**

I conduct two exercises to check robustness and explanatory power of the model. First, I test the type stationarity assumption imposed by the estimated procedure by conducting the same estimation procedure on different time periods, rather than using the full panel. Next, I fit the model to the aggregate monthly listings distribution, whose moments are not used in the estimation procedure, and compare the fit of alternative specifications.
Figure 2.12: Belief Bias Distribution by Months on Platform

Notes: Figure illustrate the estimated distribution of $\gamma_h$ by months of experience on platform. A separate estimation is run for each set of moments re-indexed by months of experience on platform.

Next, I test the stationarity assumption by dividing the panel by month and running the estimation procedure on each month of observations. For the Post-Period, I use the estimated weights from the entire Pre-Period sample and then test on the individual months in the Post-Period. The estimated parameter distributions are described in the Online Appendix. Overall, I find little variation in the estimated type distribution. This follows from the persistent distributions in listing behavior and plan choice from month to month, the two main sets of moments used in the procedure. As the moments do not significantly change, the estimated weights also do not vary much from month to month.

Finally, I compare the fit of the main specification against alternative models. First, I find the estimated weights of seller types for alternative models, which contain types without one or both of the behavioral parameters. These types of sellers would instead have a fixed parameter value (e.g., for standard beliefs, I use only seller types with $\gamma_h = 1$, and for standard dynamic response I use $\rho_h = 1$) before estimating the weights. Next, I take the estimated weights and simulate seller types, their draws, and listing behavior. Since I use within-month listings and monthly plan choices, I report the fit on the distribution of listings at the monthly level, which is not a moment used in the procedure. As plan choice moments are perfectly matched in the procedure, the fit analysis would not produce any changes among the models.

Figures 2.13(a) and 2.13(b) report the fits on the aggregate monthly listings distributions for the Pre-Period and Post-Period, respectively. Overall, the model fits the data fairly
well, capturing the general shape of both distributions. In particular, the model follows
the bunching behavior in the Post-Period, despite it not being explicitly specified in the
procedure. The relative jaggedness on part of the fit come from the discrete binning of the
seller types.

This jaggedness is further exacerbated in the alternative models, presented in Figure
2.13(c) for the Post-Period. Furthermore, the alternative specifications also underpredict the
likelihood of monthly listings below the allowance and overpredict the bunching behavior
at the allowance. Two main factors drive this result. First, the within-month variance in
listings is harder to account for when one or both of the behavioral parameters are fixed.
The behavioral parameters serve to vary the listing behavior, and without them the number
of listings from period to period is more uniform, thus leading to a larger kink and a “wavier”
distribution. Second, the behavioral parameters also rationalize a wider set of plan choices
for the same retailer parameters. With fewer types choosing each plan, each type must fit
more of the data, which leads to the increased jaggedness of the fit. Overall, the alternative
models demonstrate that adding just one of either behavioral parameter does not improve
the explanatory power of the model, but the fit is substantially better when both parameters
are incorporated.
Figure 2.13: Parameter Estimates by Months on Platform

(a) Model Fit: Monthly Listings in Pre-Period

(b) Model Fit: Monthly Listings in Post-Period

Notes: Figures illustrate the mean of the parameter estimates from the main specification by months of experience on the platform. Each point represents a separate estimation on a data sample consisting of moments re-indexed by experience.
(c) Model Fit: Alternative Specifications

Notes: Figure illustrates the percentage of monthly listing observations as a fraction of the monthly listings allowance on the Post-Period plans. The bin width is 0.025, so each point represents the percentage of observations that fall from that fraction of allowance up to 0.025 more than that fraction.
2.5 Debiasing Sellers

An important consideration when facing behavioral agents is the welfare and equilibrium impact of intervening and debiasing them. For example, one oft-used marketing policy is informing customers of suboptimal plan choices, although this is usually only done when it is profit-improving for the firm. Another example is sending regular reminders to encourage customers to act. Both of these policies have been used by eBay in the past and would serve to debias the sellers in the sample. An information treatment could potentially debias beliefs about the product values, while reminders could help sellers keep track of usage and influence the timing of listings within the month.

Table 2.3 lists the mean seller surpluses, platform revenues from listings, and aggregate listings for both the entire sample and subsets by behavioral parameter values. It also illustrates the impacts of welfare and aggregate listings from debiasing the beliefs, response to dynamic incentives, or both. The results are different for each subset of seller types since some retailer parameter combinations are more likely to fall under certain behavioral subsets.

Overall, I find a full debiasing policy, which is setting $\gamma = 1$ and $\rho = 1$, to increase average seller surplus by 6.3%, decrease revenue from listing fees by 26.4%, and leave aggregate listings unchanged for the full sample. However, the debiasing policy vary widely in efficacy among different subsets of sellers. For example, surplus can increase by as much as 20% for sellers that both underestimate ($\gamma < 1$) and respond more to the spot price ($\rho < 1$). On the other hand, the policy would do little to increase surplus for those who overestimate ($\gamma > 1$) but exhibit standard responses to dynamic incentives ($\rho = 1$). The range on the effects on platform listing revenue is even wider, as they can decrease by as much as 65% from debiasing certain sellers.

The effects of debiasing just one behavioral bias can vary significantly as well, and it can change depending on which parameter is debiased. Debiasing sellers with optimistic beliefs does not yield a greater increase in surplus than debiasing the dynamic response, since most of the surplus increase comes from choosing a small plan and is thus bounded by the fixed fees. Debiasing $\rho$ on the other hand has a significantly greater effect for most of the sellers.

One side note of potential interest is the impacts on aggregate listings. Commerce platforms may value aggregate supply as a way to increase the buyer side’s value of the platform. Furthermore, many online platforms generate the majority of their revenue from percentage fees on the supply side’s revenue (e.g., eBay and Amazon take a percentage cut on the final price of each purchase, while Uber and Lyft take percentage cuts on the final fare of the ride). Thus, platforms may deploy “targeted debiasing” as a way to increase aggregate listings without decreasing the listings from other sellers. Such a policy works by debiasing only sellers that would increase their listings. In doing so, the platform can increase the total number of listings by 4.8% and at a loss of 5.5% in listing revenue.
### Table 2.3: Seller Surplus and Debiasing from Model Estimation

<table>
<thead>
<tr>
<th>Fraction</th>
<th>Surplus ($)</th>
<th>Revenue from Listings ($)</th>
<th>Monthly Listings</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Debiasing Policy</td>
<td>Debiasing Policy</td>
<td>Debiasing Policy</td>
</tr>
<tr>
<td>γ = 1, ρ = 1</td>
<td>γ = 1</td>
<td>ρ = 1</td>
<td>γ = 1</td>
</tr>
<tr>
<td>γ = 1, ρ &gt; 1</td>
<td>0.39</td>
<td>163.45</td>
<td>163.45</td>
</tr>
<tr>
<td>γ = 1, ρ &lt; 1</td>
<td>0.18</td>
<td>118.44</td>
<td>118.44</td>
</tr>
<tr>
<td>γ &gt; 1, ρ = 1</td>
<td>0.07</td>
<td>478.61</td>
<td>478.61</td>
</tr>
<tr>
<td>γ &gt; 1, ρ &gt; 1</td>
<td>0.02</td>
<td>75.07</td>
<td>75.29</td>
</tr>
<tr>
<td>γ &gt; 1, ρ &lt; 1</td>
<td>0.20</td>
<td>130.88</td>
<td>131.15</td>
</tr>
<tr>
<td>γ &gt; 1, ρ = 1</td>
<td>0.01</td>
<td>227.22</td>
<td>230.41</td>
</tr>
<tr>
<td>γ &lt; 1, ρ = 1</td>
<td>0.04</td>
<td>136.84</td>
<td>145.30</td>
</tr>
<tr>
<td>γ &lt; 1, ρ &gt; 1</td>
<td>0.10</td>
<td>70.36</td>
<td>74.64</td>
</tr>
<tr>
<td>γ &lt; 1, ρ &lt; 1</td>
<td>0.03</td>
<td>227.39</td>
<td>240.25</td>
</tr>
<tr>
<td>Full Sample</td>
<td>1</td>
<td>160.67</td>
<td>161.92</td>
</tr>
</tbody>
</table>

Notes: Estimates are at the monthly level and weighted using the type weights estimated from the main model procedure.
2.6 Discussion and Future Work

This paper employs techniques on eliciting beliefs and responses to dynamic incentives and applies them to an online retail setting. In doing so, the analysis reveals that firms act in a manner suggestive of biased beliefs and behave in a manner inconsistent with standard models and assumptions in dynamic settings. Counterfactual analyses of debiasing firms reveal significant losses in surplus from nonstandard beliefs and behavior. Market thickness is also affected, which can be a point of concern for platforms and two-sided markets generally.

This suboptimal firm behavior may be explained by a number of potential barriers. Garicano and Rayo (2016) group many instances of organizational failures into two broad categories: perverse incentives, when individual agents within the firm have objective functions that are not in line with the firm, and bounded rationality, when agents lack the ability to optimize even if they want to do so. Sellers of all sizes are susceptible to the latter barrier, particularly if the bounded rationality originates from the firm’s decision-maker. This paper shows that individual impediments such as heuristics and behavioral biases can play a role in the decision-making process. Even the lower-volume sellers, which are less likely to have complex operations and other employees, also exhibit suboptimal behavior. However, that the majority of the suboptimal behavior originate from larger sellers seems to suggest that issues from firm governance and complexity can result in more suboptimal decisions.

There are several issues this paper does not address that I leave for future research. A limitation of this paper is the lack of explanatory power in distinguishing between the causes of organizational failures. To do so would require observations on the inputs and mechanisms within each retailer. Next, the model abstracts away from other seller decisions, most notably in two dimensions. First, the paper assumes sellers are price takers, given that many eBay listings have comparable substitutes, prices are public (subject to search costs), and other platforms compete in the same retail categories. However, in theory sellers may set prices suboptimally or according to other preferences, particularly as this paper suggests suboptimal behavior in other aspects. For example, in Backus, Blake and Tadelis (2016) the authors find use of round numbers in signaling time discounting preferences. Finally, the paper makes little mention about the extensive margins of online retail. The shift towards lowering barriers of entry and having contractors providing more services through online platforms (e.g., Uber and Airbnb) has revived interest in entry and exit models, particularly as behavioral biases and organizational failures have shown to play a role in the decision process. Both pricing decisions and entry and exit are areas for future work.
Bibliography


Hossain, Tanjim, and John Morgan. 2006. “...Plus Shipping and Handling: Revenue (Non) Equivalence in Field Experiments on eBay.” Advances in Economic Analysis & Policy, 5(2).


