Estimating Discrete Games with Many Firms and Many Decisions: An Application to Merger and Product Variety*

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Abstract

This paper presents an estimation method scalable to discrete games with many firms and many decisions. The method is applied to study merger effects on firm entry and product variety in the California retail craft beer market. Simulation results indicate that a merger, where a large brewery acquires several craft breweries, reduces product variety without efficiency gains, but increases variety with an efficiency in reducing fixed costs. Post-merger, firm entry occurs, but fails to counteract the merger's negative effects on both consumers and total surplus. The fixed cost merger efficiency reduces, but does not reverse, the negative welfare effects.

JEL: D43, L13, L41, L66
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1 Introduction

Discrete games of firm entry or product choice are often used to understand the effect of merger, divestiture, or industrial policy on market structure. In this paper, we consider the estimation of such models when there are many firms or when each firm makes a large set of discrete decisions. For example, a firm may need to choose a set of products to sell in a market from many potential products. In this case, the firm's choice can be represented as a long vector of binary decisions regarding each potential product's entry into the market. The estimation of such a model can quickly become challenging as the computational burden of solving the game increases exponentially with the number of firms and firm decisions. In this paper, we propose a computationally tractable estimation method and apply the method to study merger effects on firm entry, product variety, pricing, and welfare in the context of the craft beer market in California.

Our method is based on the bounds for conditional choice probabilities. Consider a binary action $a \in \{0, 1\}$. Assuming no equilibrium action is dominated, we can show that the equilibrium probability of $a = 1$ is larger than the probability that $a = 1$ is a dominant strategy and smaller than the probability that $a = 1$ is not a dominated strategy. These bounds hold when there is no pure-strategy equilibrium, when there are multiple equilibria, under any equilibrium selection rule, and when the selection rule varies across markets. More importantly, these bounds are easy to compute even with a large number of firms or firm decisions because the bounds can often be reduced to cumulative distribution functions evaluated at certain cutoffs. Using Monte Carlo experiments, we compare our method to existing methods for estimating discrete games. We show that as the number of firms increases, our method remains computationally feasible, while the computation time needed using existing methods increases exponentially.

We apply our method to study merger effects on firm entry and product variety. In antitrust litigation, merging parties often argue that the arrival of new entrants mitigates the increased market power resulting from a merger. One assumption behind this argument is that incumbent firms do not change their product offerings. In our paper, we study the effects of merger by addressing the following questions: Does a merger cause incumbents to add or drop products? Do new firms enter the market after a merger? What is the overall impact of product adjustments and firm entry on welfare? Do any changes in product variety offset or exacerbate the negative price effects on consumer welfare? How does a fixed cost merger efficiency influence the effect of merger on product variety?

The US craft beer industry provides an ideal empirical context to study the effects of merger on the market entry and product variety of multi-product firms. Firstly, craft breweries have recently become popular acquisition targets, and these transactions have drawn the attention of antitrust regulators (Codog, 2018). Secondly, consumer preferences for beer may vary widely, making product variety an important determinant of consumer welfare in this market. Lastly, there are rich demographic variations across geographical markets, which help to identify consumer tastes and firm costs. In our study, we focus on the state of California, which has the highest number of craft breweries and craft beer production among all US states, according to the Brewers Association, a trade group of the craft beer industry.

To address our research questions, we set up a model to describe consumer demand and firm decisions in the retail beer market in California. The demand side is a flexible random coefficient discrete choice model that allows for both observed and unobserved heterogeneity in consumer taste. The supply side is a static two-stage game. In the first stage, each firm is endowed with a set of potential products and chooses the set of products they will sell in a market. If a firm chooses not to enter the market, it chooses the empty set. In the second stage, firms observe demand and marginal cost shocks and simultaneously choose prices.

We use a newly compiled dataset to estimate our model. Our main data sources are the Nielsen Retail Scanner Data and Nielsen Consumer Panel from 2010 to 2016. We supplement these data with information on whether a beer is considered a craft beer based on the designation from the Brewers Association. We further augment our data by hand-collected information on owner identities and brewery locations.

Our demand estimates reveal substantial unobserved heterogeneity in consumer tastes and little substitution between craft and non-craft products. We obtain these estimates by combining standard macro moments with a new set of micro moments based on the panel structure of the consumer survey data. For example, to identify the dispersion in the unobservable heterogeneity in consumer tastes for craft products, we use the following intuition: if the standard deviation is large, then a household's taste for craft products is highly correlated over time. As a result, the expected total purchase of craft beers of a household in a year conditional on the household ever purchasing a craft beer in that year is large. We back out the marginal costs of beers based on the first-order conditions following the standard approach.

We apply our method based on bounds for conditional choice probabilities to estimate the fixed cost of product entry. This method is well suited to our empirical setting, which features many firms and many potential products. Our empirical setting also features rich market- and product/market-level variations resulting in variations in our bounds. Applying our method, we find higher fixed costs of entry for products by independent craft breweries. We also find that both the mean fixed cost of entry and the variance of the fixed cost shock increase with market size.

Using the estimated model, we conduct a counterfactual simulation where the largest macro brewery acquires three large craft breweries. This hypothetical merger case allows us to examine what would happen if the current acquisition trend (i.e., a so-called macro beer firm acquires small craft breweries) continues to the point where the craft beer market becomes as concentrated as the overall beer market. In our simulations, we find that whether merging firms add or drop products depends on whether a merger efficiency in reducing fixed costs is considered. Without the merger efficiency, the merged firm drops products; with the merger efficiency, the merged firm adds products, leading to an overall increase in product variety. We also find that, in both scenarios, the merger causes both new firm entry and new product entry by non-merging incumbents. However, their effects are not enough to offset the negative effect of the merger on both consumer surplus and total surplus. The merger efficiency mitigates but does not reverse the overall welfare loss.

Contributions and Literature Review This paper makes two contributions to the literature. First, we develop a method for estimating discrete choice games with many firms and many decisions. Our method differs from existing methods for estimating discrete games, such as Aradillas-Lopez and Tamer (2008) and Ciliberto and Tamer (2009), in the construction of bounds.[1] These papers use bounds defined by the probability that a market-level outcome is a unique equilibrium. For example, the probability that an outcome is an equilibrium is larger than the probability that this outcome is a unique equilibrium. Computing such bounds, therefore, requires enumerating all possible outcomes (e.g., all possible entry outcomes regarding each potential entrant's entry decision) and checking whether each one of them is consistent with the behavioral assumption of the model (e.g., Nash equilibrium). Since the number of possible outcomes increases exponentially with the number of firms, the computational burden may become prohibitively high in settings with many firms. By contrast, our bounds are one-dimensional cumulative distribution functions evaluated at certain cutoffs. Computing these cutoffs does not require solving the full game. Therefore, our method is scalable to settings with many firms and firm decisions.

Another strand of the literature on estimating discrete games exploits moment inequalities derived from a necessary equilibrium condition that no firm has an incentive to unilaterally deviate from the observed equilibrium. These papers typically rely on a mean-zero assumption of non-structural errors (Ho, 2009; Pakes, Porter, Ho and Ishii, 2015; Wollmann, 2018) or support restrictions (Eizenberg, 2014), and do not estimate the distribution of the structural errors associated with the discrete actions. Our approach estimates the structural

[1] Our bounds and the bounds in these papers are not sharp. See Beresteanu, Molchanov and Molinari (2011), Galichon and Henry (2011), and Chesher and Rosen (2017) for characterizations of the sharp identification region.

error distribution and takes it into account in our counterfactual simulations.

Overall, our approach to estimating discrete games is scalable to large games and has advantages when solving for equilibria is costly and when it is important to consider shocks that are known to firms but unobservable to researchers.[2]

Second, we contribute to the literature on merger, entry response, and product variety. One strand of the literature studies the entry defense both theoretically (e.g., Spector, 2003; Anderson, Erkal and Piccinin, 2020; Caradonna, Miller and Sheu, 2021) as well as through simulations and empirical studies (e.g., Werden and Froeb, 1998; Cabral, 2003; Gandhi, Froeb, Tschantz and Werden, 2008; Ciliberto, Murry and Tamer, 2021). We contribute to this strand of the literature by expanding the examination to multi-product firms with endogenous product choice. In our model, because incumbents can reduce product offerings, it is possible for a merger to decrease product variety while inducing new entry.

Another strand within this literature studies how a merger affects product variety and welfare when there is no firm entry (e.g., Fan, 2013; Wollmann, 2018; Fan and Yang, 2020; Garrido, 2020; Li, Mazur, Park, Roberts, Sweeting and Zhang, 2022).[3] We contribute to this strand of the literature by jointly studying firm entry responses and incumbent product adjustments after a merger to quantify the net changes in product variety.

We also contribute to understanding how merger efficiency shapes the effects of mergers. While Fan (2013) considers cost synergies in operation costs in the newspaper industry and Elliott, Houngbonon, Ivaldi and Scott (2021) study how economies of scale affect product quality and firm investment in the telecommunications industry, this paper examines a merger efficiency in reducing fixed costs and shows that even though the merger efficiency can lead to an increase in product variety, such a change only mitigates but does not reverse

[2] There are four other alternative estimation approaches. First, one can obtain a unique equilibrium with additional assumptions and estimate the model via maximum likelihood (Reiss and Spiller, 1989; Garrido, 2020) or a simulated method of moments (Berry, 1992; Li, Mazur, Park, Roberts, Sweeting and Zhang, 2022). Second, Illanes (2017) estimates a dynamic discrete choice problem using a semi-parametric latent variable integration method (Schennach, 2014). This approach also avoids solving a game or an optimization problem, but depends on the availability of certain instruments and, in their absence, can result in relatively wide (and sometimes unbounded) confidence sets of parameters. Third, in their merger simulations, Fan and Yang (2020) make direct assumptions about the distribution of an unobserved fixed cost shock conditional on the observed equilibrium. In comparison, the approach in this paper estimates the distribution. Finally, in a contemporaneous paper, Wang (2020) proposes a hybrid approach that replaces one side of the Ciliberto and Tamer (2009) bounds with probability bounds based on the concept of dominant strategies. The computational burden of such an approach lies between our method and that of Ciliberto and Tamer (2009), but still cannot scale because the number of outcomes for which one needs to construct the bounds still increases exponentially in the number of firms and decisions.

[3] Several papers (e.g., Berry and Waldfogel, 2001; Sweeting, 2010; Jeziorski, 2015) have studied merger effects on firm entry and product variety in the radio industry but do not quantify the impact of mergers on consumer welfare since radio stations do not set prices for their listeners. Seim (2006) and Draganska, Mazzeo and Seim (2009) also study entry with endogenous product choice but within the context of an incomplete information framework.

the merger's negative welfare effects.

The rest of the paper is organized as follows. Section 2 explains our estimation method and presents our Monte Carlo simulation results. Section 3 describes the craft beer market in California and our data. Section 4 presents the empirical model, and Section 5 explains the estimation procedure. Section 6 presents the estimation results. Section 7 discusses the counterfactual designs and results. Finally, Section 8 explains two robustness analyses, and Section 9 concludes.

2 Discrete Games and Our Estimation Strategy

The estimation of discrete games carries several challenges. First, since there might be multiple equilibria, the maximum likelihood approach may not apply without explicit equilibrium selection rules.[4] Second, a selection issue may complicate a moment inequality approach because the distributions of unobservables conditional on observed actions differ across these actions. We have discussed the existing methods dealing with these issues in the literature review part of the Introduction. In this section, we present our method by starting with a simple model to illustrate how we define our bounds. We then explain our estimation strategy for more general models. We conclude this section with a set of Monte Carlo experiments to compare our approach to existing methods.

2.1 An Illustrative Model and Our Bounds

To illustrate our bounds, we start with a 2×2 model with two firms where each firm makes a single binary decision. We later extend the model to a setting with more firms where each firm makes a vector of binary decisions. In this bivariate model, firms 1 and 2 decide whether to enter market m. Let $Y_{nm} = 1$ indicate entry by firm n in market m. If firm n enters, its profit is $\pi_{nm}(Y_{-nm}) - C_{nm} - \zeta_{nm}$, where $\pi_{nm}(Y_{-nm})$ is a variable profit function that depends on the rival action Y_{-nm}, C_{nm} is the fixed cost of entry, and ζ_{nm} is a fixed cost shock observable to firms. It follows a distribution, F_ζ. Firm n enters market m if and only if its post-entry profit is positive, i.e.,

$$Y_{nm} = \mathbb{1}\left[\pi_{nm}(Y_{-nm}) - C_{nm} - \zeta_{nm} \geq 0\right]. \tag{1}$$

Our firm behavior assumption is as follows:

Assumption 1. *Y_{nm} is not a dominated strategy for n= 1 or 2.*

[4] One exception is that Tamer (2003) considers a maximum likelihood estimator in the presence of multiple equilibria for bivariate games without specifying an equilibrium selection rule.

In other words, we assume that any observed Y_{nm} is not dominated. This level-1 rationality assumption implies the following bounds for $\Pr(Y_{nm}=1)$:

$$\begin{aligned} &\Pr(Y_{nm}=1 \text{ is a dominant strategy}) \\ \leq &\Pr(Y_{nm}=1) \\ \leq &\Pr(Y_{nm}=1 \text{ is not a dominated strategy}). \end{aligned} \tag{2}$$

Given that $Y_{nm}=1$ is a dominant strategy if and only if $\zeta_{nm} < \min\{\pi_{nm}(0), \pi_{nm}(1)\} - C_{nm}$, and that $Y_{nm}=1$ is not a dominated strategy if and only if $\zeta_{nm} < \max\{\pi_{nm}(0), \pi_{nm}(1)\} - C_{nm}$, it follows from (2) that

$$F_\zeta(\min\{\pi_{nm}(0), \pi_{nm}(1)\} - C_{nm}) \leq \Pr(Y_{nm}=1) \leq F_\zeta(\max\{\pi_{nm}(0), \pi_{nm}(1)\} - C_{nm}).$$

Under the assumption that the entry of the rival reduces a firm's profit, the inequality can be further reduced to

$$F_\zeta(\pi_{nm}(1) - C_{nm}) \leq \Pr(Y_{nm}=1) \leq F_\zeta(\pi_{nm}(0) - C_{nm}).$$

Before we discuss the general model and estimation, we first highlight the advantages of our bounds and compare our bounds with those in the literature.

Advantages of Our Bounds

There are two advantages of using our bounds for estimating discrete games. First, our bounds do not rely on equilibrium selection assumptions. Specifically, they hold when there are multiple equilibria, when the equilibrium selection mechanisms differ across markets, or when there is no pure strategy equilibrium for some values of fixed cost shocks. Second, since our bounds are one-dimensional CDFs, they are easy to compute. Therefore, the key advantage of using our bounds for estimating discrete games is that it is computationally feasible even for settings with many firms and when each firm makes multiple binary decisions simultaneously (such as product portfolio decisions).

Our bounds are also intuitive. In a single-agent binary choice model, the inequalities collapse into an equality used in the standard GMM estimator (McFadden, 1989). Thus, our approach can be considered an extension of the GMM estimation of binary choice models to a game setting.

Comparison to Bounds in the Literature

Ciliberto and Tamer (2009) Ciliberto and Tamer (2009) (henceforth, CT) assume the outcomes observed in the data are pure-strategy Nash equilibria and construct bounds for the probability of observing an outcome (Y_{1m}, Y_{2m}), denoted by $\Pr(Y_{1m}, Y_{2m})$, as follows:

$$\begin{aligned} &\Pr\left((Y_{1m}, Y_{2m}) \text{ is a unique pure-strategy Nash equilibrium}\right) \\ \leq &\Pr\left(Y_{1m}, Y_{2m}\right) \\ \leq &\Pr\left((Y_{1m}, Y_{2m}) \text{ is a pure-strategy Nash equilibrium}\right). \end{aligned} \tag{3}$$

The CT bounds are sharper than ours. We provide a graphic illustration of this comparison in Supplemental Appendix A. The intuition is that $Y_{1m} = 1$ being a dominant strategy is a sufficient but not necessary condition for the event that either $(Y_{1m} = 1, Y_{2m} = 1)$ or $(Y_{1m} = 1, Y_{2m} = 0)$ is a unique Nash equilibrium. Therefore, we have

$$\begin{aligned} &\Pr\left(Y_{1m} = 1 \text{ is a dominant strategy}\right) \\ \leq &\Pr\left((Y_{1m} = 1, Y_{2m} = 1) \text{ is a unique pure-strategy Nash equilibrium}\right) \\ + &\Pr\left((Y_{1m} = 1, Y_{2m} = 0) \text{ is a unique pure-strategy Nash equilibrium}\right) \end{aligned}$$

In other words, the CT bounds imply a larger lower bound for $\Pr(Y_{1m} = 1)$ than our lower bound. Similarly, the CT bounds also imply a smaller upper bound than ours.

However, using the CT bounds for estimation in practice can be computationally challenging. First, one needs to obtain the bounds for all possible entry outcomes. With N firms making binary entry decisions, there are 2^N possible outcomes. Second, to simulate the lower bound for each outcome (i.e., the probability that this outcome is a unique equilibrium), one has to draw fixed cost shocks (ζ_{1m}, ζ_{2m}) and, for each draw, find all equilibria by going over all possible outcomes and verifying whether each one of them is an equilibrium. This procedure can be computationally costly, especially when there are many firms, as the number of possible outcomes increases exponentially with the number of firms.

Aradillas-Lopez and Tamer (2008) Similarly to CT, Aradillas-Lopez and Tamer (2008) (henceforth, AT) also construct bounds for $\Pr(Y_{1m}, Y_{2m})$ but consider weaker assumptions than Nash. Here we focus on the AT bounds based on the level-1 rationality assumption. Unlike the comparison between the CT bounds and our bounds, the AT bounds are not necessarily sharper than ours (and vice versa). For example, $Y_{1m} = 1$ being a dominant strategy does not necessarily imply that either $(Y_{1m} = 1, Y_{2m} = 1)$ or $(Y_{1m} = 1, Y_{2m} = 0)$ is a unique model implication according to level-1 rationality. In Supplemental Appendix A, we explain in detail the model implications that our bounds exploit but the AT bounds do not.

Computationally, one still has to construct bounds for all possible entry outcomes, making it challenging to estimate a discrete game in settings with many firms.

2.2 General Models and Estimation Using Our Bounds

In this section, we describe a general model and explain how to estimate the model using our bounds. We consider M markets and N firms, where each firm n makes a vector of binary decisions, Y_{nm}, in each market m. For example, firms decide whether to enter a market and, if so, which subset of products from a potential set of products to sell. In this setting, $Y_{nm} = (Y_{jm}, j \in \mathcal{J}_n)$, where $\mathcal{J}_n$ is the set of potential products for firm n, and $Y_{jm} \in \{0, 1\}$ indicates whether firm n sells product j in market m. Note that each product j is firm-specific.

We use $Y_m = (Y_{nm}, n = 1, ..., N)$ to denote all firm decisions in the market, and $\pi_n(Y_m, X_{nm})$ to denote the variable profit function of firm n, which depends on Y_m as well as a set of observable covariates, X_{nm}. We further assume that there is a cost associated with choosing $Y_{jm} = 1$. This cost is $c(W_{jm}, \theta) + \zeta_{jm}$, where W_{jm} is a set of exogenous covariates. The unobserved cost shock, ζ_{jm}, is assumed to be i.i.d. and follows the distribution $F_\zeta(\cdot, \sigma_\zeta)$.

The parameters to be estimated include the coefficients θ and the distribution parameters σ_ζ in the fixed cost. Researchers observe (Y_{jm}, W_{jm}, X_{nm}), but not the fixed cost shock ζ_{jm}. The variable profit function $\pi_n(Y_m, X_{nm})$ is either known or has been estimated. For example, one could follow the standard literature in Industrial Organization to estimate demand and marginal costs and then obtain the estimated variable profit at a Nash-Bertrand equilibrium for any given Y_m.

We define the change in a firm's variable profit when Y_{jm} turns from 0 to 1:

$$\mathit{\Delta}_j(Y_{-jm}, X_{nm}) = \pi_n(Y_{jm} = 1, Y_{-jm}, X_{nm}) - \pi_n(Y_{jm} = 0, Y_{-jm}, X_{nm}), \tag{4}$$

where $Y_{-jm} = (Y_{j'm}, j' \in \cup_n \mathcal{J}_n, j' \neq j)$. Given the discrete nature of Y_{-jm}, the following minimum and maximum changes in variable profits exist: $\underline{\mathit{\Delta}}_j(X_{nm}) = \min_{Y_{-jm}} \mathit{\Delta}_j(Y_{-jm}, X_{nm})$ and $\overline{\mathit{\Delta}}_j(X_{nm}) = \max_{Y_{-jm}} \mathit{\Delta}_j(Y_{-jm}, X_{nm})$.

Following the discussion in the previous section, we can see that the bounds of the conditional probability $Y_{jm} = 1$ given X_{nm} and W_{jm} are:

$$\begin{aligned} & F_\zeta\left(\underline{\mathit{\Delta}}_j(X_{nm}) - c(W_{jm}, \theta), \sigma_\zeta\right) \\ & \leq \Pr(Y_{jm} = 1 \,|X_{nm}, W_{jm}) \\ & \leq F_\zeta\left(\overline{\mathit{\Delta}}_j(X_{nm}) - c(W_{jm}, \theta), \sigma_\zeta\right). \end{aligned} \tag{5}$$

We define the following moment functions:

$$
\begin{aligned}
L\left(Y_{jm}, X_{nm}, W_{jm}, \theta, \sigma_\zeta\right) &= F_\zeta\left(\underline{\Delta}_j\left(X_{nm}\right) - c\left(W_{jm}, \theta\right), \sigma_\zeta\right) - \mathbb{1}\left(Y_{jm} = 1\right), \\
H\left(Y_{jm}, X_{nm}, W_{jm}, \theta, \sigma_\zeta\right) &= \mathbb{1}\left(Y_{jm} = 1\right) - F_\zeta\left(\overline{\Delta}_j\left(X_{nm}\right) - c\left(W_{jm}, \theta\right), \sigma_\zeta\right).
\end{aligned} \tag{6}
$$

The inequalities in (5) imply the following conditional moment inequalities:

$$
\begin{aligned}
E\left(L\left(Y_{jm}, X_{nm}, W_{jm}, \theta, \sigma_\zeta\right) | X_{nm}, W_{jm}\right) &\leq 0, \\
E\left(H\left(Y_{jm}, X_{nm}, W_{jm}, \theta, \sigma_\zeta\right) | X_{nm}, W_{jm}\right) &\leq 0.
\end{aligned} \tag{7}
$$

We construct the confidence set for (θ, σ_ζ) based on the inequalities in (7) following the literature on inference using moment inequalities. Details on our construction of the confidence set are given in Supplemental Appendix B.

Identification The identification of (θ, σ_ζ) based on the inequalities in (5) is similar to the idea of special regressors in entry games (Ciliberto and Tamer, 2009; Lewbel, 2019). To identify our parameters, we exploit exogenous variations in X_{nm} and W_{jm}. For example, to identify the coefficient in θ that corresponds to an indicator variable, we compare the entry probability conditional on this indicator being 1 versus 0, holding other covariates fixed. Similarly, to identify the coefficient of a continuous variable, we examine how entry probability varies across different ranges of the continuous variable. Exogenous variations in X_{nm} and W_{jm} are also helpful for identifying the distribution parameters σ_ζ. For example, consider a distribution of ζ_{jm} that is fully specified by its variance. If the variance is large, the upper and lower bounds will show little co-variance with the covariates. In the special case where ζ_{jm} follows a symmetric distribution, both bounds in (5) approach 0.5 (a constant) as the variance increases. On the other hand, when the variance is close to 0, both bounds are close to 0 if $\overline{\Delta}_j\left(X_{nm}\right) - c\left(W_{jm}, \theta\right) < 0$ or close to 1 if $\underline{\Delta}_j\left(X_{nm}\right) - c\left(W_{jm}, \theta\right) > 0$, by Chebyshev's Inequality. Therefore, if the variance is small, the model predicts large jumps in entry probabilities even with small changes in the covariates. Both the lack of sensitivity of entry probability to covariates (in the case of a large variance of ζ_{jm}) and the high sensitivity (in the case of a small variance) can be tested by data.

Extensions Here, we assume that the total cost associated with a vector of binary decisions is the sum of the cost associated with each decision. In Supplemental Appendix F, we extend our method to estimate a model allowing for economies or diseconomies of scope. In this extension, we additionally consider bounds for the probability that a firm has at least one product in a market. Here, we also assume that the unobservable cost shock is i.i.d. In Supplemental Appendix G, we extend our method to estimate correlations in unobservable cost shocks. In this extension, we add bounds for the joint probability that two products are both in a market.

2.3 Monte Carlo Experiments

We use Monte Carlo experiments to compare both the performance and the computational burden of our method with those in the literature.

2.3.1 Monte Carlo Experiment Setup

In our Monte Carlo experiments, we consider an entry game similar to that in Ciliberto and Tamer (2009). Specifically, there are N potential entrants and each firm n makes a binary decision $Y_{nm} \in \{0, 1\}$, where $Y_{nm} = 1$ represents entering market m. If firm n enters, its variable profit is:

$$\pi_n(Y_{-nm}, X_{nm}) = O_m + x_{nm} - 0.5 \sum_{n' \neq n} x_{n'm} Y_{n'm},$$

where $Y_{-nm} = (Y_{n'm}, n' \neq n)$ denotes rival firms' entry decisions, O_m represents a market-level profit shifter, and x_{nm} is a firm-level profit shifter. We assume that the competitive impact of firm n' on other firms' profits is $0.5x_{n'm}$. We collect all these covariates in X_{nm}.

The fixed cost of entry is $C + \sigma\zeta_{nm}$, where the unobservable cost shock ζ_{nm} is assumed to be a standard normal random variable and i.i.d across both firms and markets. The mean fixed cost parameter C and the standard deviation σ are the parameters to be estimated. We set the true values to be $C = \sigma = 1$.

For each Monte Carlo experiment, we simulate 500 data sets and each data set consists of 5000 markets. To simulate a data set, we draw X_{nm} for each firm and each market. Specifically, we draw O_m uniformly between 0 and 0.3 and x_{nm} uniformly between 0 and 1. We draw ζ_{nm} from the standard normal distribution. We compute the Nash equilibrium entry outcome for each market. In the case of multiple equilibria, an equilibrium is selected at random with equal probability.

Since the profit function π_n decreases in the entry decision of a firm's rivals, we have

$$\min_{Y_{-nm}} \pi_n(Y_{-nm}, X_{nm}) = \pi_n((1, ..., 1), X_{nm}) = O_m + x_{nm} - 0.5 \textstyle\sum_{n' \neq n} x_{n'm},$$
$$\max_{Y_{-nm}} \pi_n(Y_{-nm}, X_{nm}) = \pi_n((0, ..., 0), X_{nm}) = O_m + x_{nm}.$$

Based on (5), we use the following bounds in our estimation:

$$\Phi\left(\left[O_m + x_{nm} - 0.5\sum\nolimits_{n'\neq n} x_{n'm} - C\right]/\sigma\right) \leq \Pr\left(Y_{nm} = 1\,|X_{nm}\right) \leq \Phi\left(\left[O_m + x_{nm} - C\right]/\sigma\right),$$

where $\Phi(\cdot)$ is the standard normal distribution function.

2.3.2 Monte Carlo Experiment Results

We first present the coverage probability of our 95% confidence set containing parameter values of C and σ in the neighborhood of the true parameter value (i.e., $(C, \sigma) = (1, 1)$).[5] Specifically, for visibility, we plot the coverage probabilities for C and σ separately. For instance, for the coverage probability of $C = 0.8$ (i.e. $C - C_{\text{true}} = -0.2$), we report the fraction of the 500 data sets where the 95% confidence set corresponding to this data set contains $(0.8, \sigma)$ for some value of σ. We do so for candidate values of C from 0 to 2 and σ from 0 to 2.

Figure 1: Coverage Probabilities Using Our Bounds vs. the CT and AT Bounds

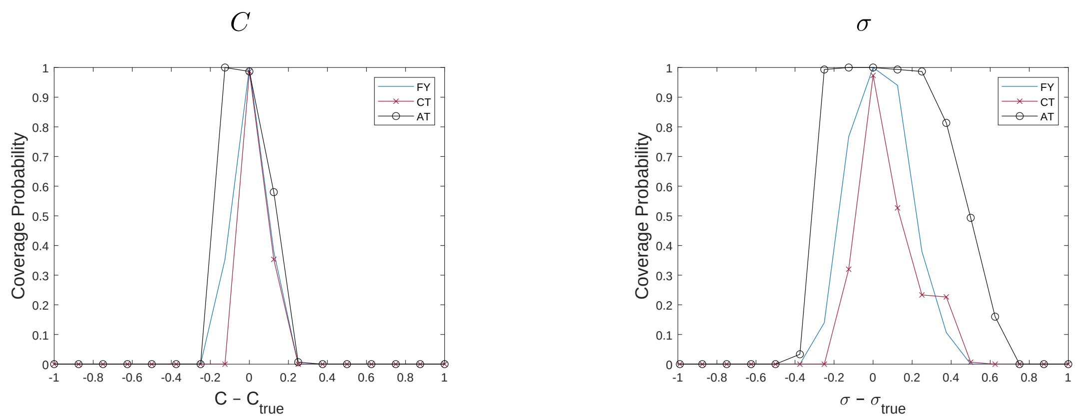


Figure 1 compares the coverage probabilities using our bounds versus the CT and AT bounds and shows that the CT bounds outperform our bounds, and our bounds outperform the AT bounds. From this figure, we can see that using all three bounds, the coverage probability for a parameter value in the neighborhood of the true parameter value decreases for parameter values further away from the true value. Comparing the coverage probabilities based on the three bounds, we find that the coverage probabilities based on our bounds (labeled FY) are larger than those based on the CT bounds but smaller than those based on the AT bounds. This finding is consistent with our discussion on the comparison of our

[5]We construct our confidence set following Andrews and Soares (2010). As mentioned, details on the inference procedure are explained in Supplemental Appendix B.

Table 1: Comparison to CT and AT Bounds: Computation Time

N (#Firms)	FY (s)	CT (s)	AT (s)
2	0.031	0.224	0.032
3	0.031	1.024	0.187
4	0.032	3.705	1.285
5	0.032	16.341	10.026

Note: the table reports the computation time required to evaluate the test statistic used for constructing the confidence set once. The three columns correspond to our bounds (FY), the Ciliberto and Tamer (2009) (CT) bounds, and the Aradillas-Lopez and Tamer (2008) (AT) bounds.

bounds to the CT and AT bounds in Section 2.1, i.e., while the CT bounds are sharper than ours, there is no clear ranking between our bounds and the AT bounds.

We then compare the computational burden of the three methods. To this end, we report the time needed to evaluate the test statistic used for constructing the confidence set. Specifically, we compare the time needed to compute the test statistic once using our bounds versus the CT and AT bounds in Table 1.[6]

Table 1 shows that our method comes with a computational advantage that grows exponentially with the number of firms in a game. Comparing the three columns in the table, we can see that the computation time for evaluating the test statistic once based on our FY bounds is consistently smaller than that using the CT and AT bounds. Moving from the first row to the last row in the table, we can see that the computation time for computing the test statistic based on our FY bounds remains stable as the number of potential entrants increases. In contrast, the computation time using the CT and AT bounds increases from 0.224 seconds to 16 seconds and from 0.032 seconds to 10 seconds, respectively. This is not surprising because evaluating our moment functions only involves evaluating one-dimensional CDFs. However, evaluating the moment functions based on the CT and the AT bounds requires computing bounds for all possible market outcomes, the number of which increases exponentially as the number of firms increases.

We end this section with a further discussion on the computational advantage of our method and the tightness of our bounds. The computational advantage is greater when there are many firms. At the same time, the gap between our lower and upper bounds is also greater in settings with many firms. Therefore, there is a trade-off between the identifying power and the computational advantage of our bounds. It is worth noting that as the number of firms increases, while the computational advantage increases exponentially, we expect the gap between our bounds to increase at a lower, possibly diminishing, rate. For

[6]The results are computed on an Intel Broadwell EP (E5-2680 v4, 2.4 GHz). We use 100 simulation draws of (ζ_{1m}, ζ_{2m}) to simulate the CT bounds.

example, the profit difference between a duopolist and a triopolist is typically smaller than that between a monopolist and a duopolist.[7] As a result, having a large number of firms does not necessarily mean our bounds are too wide to be useful. Moreover, the tightness of the bounds also depends on the nature of competition between firms and is ultimately an empirical question.

3 Empirical Background and Data

We apply our method to study merger effects on firm entry and product variety in the retail craft beer market in California.[8] According to the 2015 Brewers Association estimates, California accounted for 18% of craft beer volume and 12% of craft breweries in the nation, the highest among all US states. California has its own tied-house laws that expand on federal statues prohibiting "tied-houses".[9] In addition, California passed competition laws that further prohibit payments for stocking products (Croxall, 2019). These laws prohibit practices that hinder the entry of craft breweries into the retailer market and thus motivate our assumption that breweries make their own entry and product variety decisions. This simplification keeps our model tractable.

Our analysis is based on a new dataset that we compiled from various sources. The primary datasets are the market-level data in the Nielsen Retail Scanner Data and the micro-level panel data in the Nielsen Consumer Panel between 2010 and 2016. We define a product to be a brand in the Nielsen data (e.g., Samuel Adams Boston Lager). We aggregate the Nielsen scanner data from its original UPC/week level into a product/month-level dataset by homogenizing the size of a product (a unit represents a 12-ounce-12-pack equivalent), adding quantities across weeks within a month, and using the quantity-weighted average price across weeks within a month as a given product's price in a given month. We then supplement the dataset with information on whether a beer is considered a craft beer based on the designation by the Brewers Association. We also add hand-collected data on the identities of the corporate owner and the brewery as well as the location of the production facility for each product in our dataset. For example, Samuel Adams Boston Lager is produced at the

[7] See Bresnahan and Reiss (1991) for an early work establishing this result. Berry (1992) specifies and estimates a profit function linear in the logarithm of the number of firms to capture the diminishing competition effect as the number of firms increases.

[8] There has been growing interest in the market structure of the craft beer industry. For example, Tremblay, Iwasaki and Tremblay (2005) document the entry of microbreweries in the US. Elzinga and McGlothlin (2021) analyze a macro brewery's acquisition of a craft brewery. Bronnenberg, Dubé and Joo (2022) study the formation of preferences for craft beer and its implication for the future market structure of the industry.

[9] "Tied-houses" refer to vertical relationships between manufacturers and retailers that exclude small manufacturers such as craft breweries from placing their products with retailers.

Samuel Adams Boston Brewery in Boston and owned by the Boston Beer Company. We define a firm as a corporate owner (e.g., Boston Beer Company). A firm can own multiple breweries and products. Finally, we merge the data with county demographics obtained from the US Census.

In our analysis, we define a market as a retailer-county pair. The Nielsen consumer panel data suggest that cross-retailer shopping is rare. For example, we find that over 80% of households in our study purchase all their beer from one retailer-county combination in 2016. This finding is consistent with those of Huang, Ellickson and Lovett (2022) and Illanes and Moshary (2020), who find little evidence of retailer competition in the spirits category. In our estimation, we define market size as the average monthly alcohol sales in a market (in the unit of a 12-ounce-12-pack equivalent) multiplied by 8, which is the average number of household trips per month in the panel data.[10]

We consider a product to be available in a market in a calendar year if the product's monthly sales are more than 20 units for more than 6 months in the market in the year. Moreover, for craft products, we keep those produced by the top 60 craft breweries according to their national volumes in the 2015 Brewers Association production data. We thus focus on breweries established in the 1990s or earlier. In the end, our sample covers 83% of California's craft beer quantity in the Nielsen Scanner Data across our sample periods.[11]

We define a firm's set of potential products in a year as all products owned by the firm available in any market in the year. Note that we do not consider new brewery or brand creation but rather focus on a firm's decision to sell an existing product in a market, a decision far less costly than a *de novo* entry.[12] Therefore, our setting can be considered favorable for firm or product entry. As we see later, even in this favorable setting where new entrants bring in new products, the merger effect on consumer welfare is negative.

Table 2 reports summary statistics based on 110 markets present in the data every year from 2010 to 2016. These markets account for 82% of the total quantity from all markets and years. The table shows that the annual craft beer sales in the sample are, on average, about 5 million units, which accounts for roughly 10% of total beer sales for a given year. The average price for craft beer is around 17 dollars per unit in 2016 dollars, which is higher

[10] Our results are robust to alternative scaling factors.

[11] Although our retail data precludes a direct comparison of the retail beer market with the "on-premises" market (such as taprooms, bars, and restaurants), the Brewers Association estimates that the retail channel accounts for 65% of craft beer volume (Watson, 2016). Likely due to similar data limitations, previous research on the beer industry has also focused on the retail segment (Ashenfelter, Hosken and Weinberg, 2015; Asker, 2016; Miller and Weinberg, 2017; Miller, Sheu and Weinberg, 2021).

[12] Defining what kind of new products a beer firm could create is difficult. Moreover, it is infeasible to obtain an estimate of the product fixed effect in our demand and marginal cost specifications for non-existent products.

Table 2: Annual Total Quantity, Prices, and Numbers of Firms and Products

	Total Quantity (12-oz 12-pk equiv)	Avg. Price (2016 $)	# Firms Per Year	# Products Per Year
Craft	4,914,209	17	36	135
All	53,465,658	11	54	269

Note: for each year from 2010 to 2016, we first calculate a year's total and craft beer quantities, quantity-weighted average prices, number of firms and number of products, and then take the average across years.

Table 3: Shares of Total Quantity and Number of Products by Beer Types

		Ale	Lager	Light
Quantity				
	Craft	71.53%	27.13%	0.44%
	All	12.50%	46.42%	40.02%
Number of products				
	Craft	66.33%	26.87%	0.41%
	All	44.19%	39.76%	7.23%

Note: the shares reflect the respective proportions of the total quantity from 2010 to 2016, or of the total number of unique products in these years.

than the average beer price of 11 dollars per unit. Although craft beer sales account for only 10% of the total market, the number of craft firms and products make up more than half of the market.

Table 3 provides a breakdown of the sales and number of products by beer types. Among craft products, ales constitute 66% of the product counts and 72% of sales. Lagers account for 27% and 46% of the craft and overall beer market share, respectively. While light beers account for 40% of the overall beer sales, their market share within craft products is only 0.44%, and this pattern has remained stable over time.

A key primitive in the product variety decisions is the fixed cost of product entry. According to our interviews with industry experts,[13] the main cost of product entry is a flow cost of the marketing support that a firm needs to provide to a retailer in a local market. By contrast, the sunk cost of convincing a retailer to carry a brewery's products or contracting with a distributor seems negligible compared to the fixed cost of marketing support. For the craft products studied in this paper, it is illegal at both the federal and state level and extremely rare for grocers or distributors to charge slotting fees.

[13] They are the Chief Economist, Bart Watson, and the General Counsel, Marc Sorini, at the Brewers Association.

4 Model

4.1 Demand

We use a random coefficient discrete choice model to describe consumer demand for beer. A product's characteristics include its flavor type (ale, lager, light, and others),[14] whether it is imported from outside North America, and whether it is designated as a craft product. Note that these characteristics can overlap. For example, Bud Light is a light, North American, non-craft beer, while Samuel Adams Lager is a lager, North American, craft beer. These characteristics of product j are captured by a vector of indicator variables $\boldsymbol{x}_j = \left(x^{\text{ale}}, x_j^{\text{lager}}, x_j^{\text{light}}, x_j^{\text{import}}, x_j^{\text{craft}}\right)$. We allow both household income and unobservable heterogeneity to affect preferences. We specify the utility function of household i in market m from product j in month t as

$$\begin{aligned} u_{ijmt} = &(\sigma_0 \nu_i + \kappa_0 y_i) + (\alpha + \kappa_\alpha y_i)\, p_{jmt} \\ &+ \sigma^{\text{ale}} \nu_i^{\text{ale}} x_j^{\text{ale}} + \sigma^{\text{lager}} \nu_i^{\text{lager}} x_j^{\text{lager}} + \sigma^{\text{light}} \nu_i^{\text{light}} x_j^{\text{light}} \\ &+ \sigma^{\text{import}} \nu_i^{\text{import}} x_j^{\text{import}} + (\sigma^{\text{craft}} \nu_i^{\text{craft}} + \kappa^{\text{craft}} y_i) x_j^{\text{craft}} \\ &+ \beta X_{jm} + FE_j^{\text{demand}} + FE_m^{\text{demand}} + FE_t^{\text{demand}} + \xi_{jmt} + \varepsilon_{ijmt}, \end{aligned} \tag{8}$$

where y_i is the natural logarithm of household i's annual income and $\nu_i^{(\cdot)}$ is the household-specific unobserved taste shock, which follows a normal distribution and is independent across households. Therefore, the σ parameters capture the dispersion in unobserved household tastes while the κ parameters measure the effect of household income on tastes and the price coefficient. Note that we do not include mean coefficients for $\boldsymbol{x}_j$ because they are absorbed in product fixed effects. The covariates X_{jm} represent a set of indicator functions for whether the distance from the brewery's nearest production facility to the market falls within a certain distance range. Distance potentially plays an important role in demand as a local beer may lack name recognition outside of its local market (see, for example, Tamayo, 2009). We also include in our model product fixed effects FE_j^{demand}, market fixed effects FE_m^{demand}, and month fixed effects FE_t^{demand} to capture unobserved factors that may vary at these levels. The error term ξ_{jmt}, therefore, captures the transient, month-to-month variations of demand shocks specific to a product, market, and month combination. Finally, the last term in (8), ε_{ijmt}, is a household's idiosyncratic taste, which is assumed to be i.i.d. and follows a type-1 extreme value distribution.

Overall, our demand specification gives us the market share $s_{jmt}\left(p_{jmt}, p_{-jmt}\right)$ of product

[14] Some examples in the category of "others" include stout, porter, and near beers, which collectively account for 0.9% of the craft quantities.

j in month t and market m, where p_{-jmt} is a vector of the prices of all other products in market m and month t. Other determinants of demand (product characteristics, fixed effects, and demand shocks of all products in the market) are absorbed by the subscript jmt of the function $s_{jmt}(\cdot, \cdot)$. Multiplying the market share by the corresponding market size then gives us the demand for product j, $D_{jmt}(p_{jmt}, p_{-jmt})$.

4.2 Supply

The supply side describes firms' product and price decisions. In each market, firms simultaneously choose which beer products, if any, to sell. This product choice is made at the beginning of each year τ and is fixed throughout the year. Then, in each month t, firms simultaneously choose the retail prices for their products.

Specifically, we model the supply side as a two-stage static game. In the first stage, at the beginning of year τ, firms observe fixed costs for all potential products and simultaneously decide on a set of products to offer in market m. In the second stage, at the beginning of month t, the demand and marginal cost shocks $(\xi_{jmt}, \omega_{jmt})$ are realized, and firms choose the retail prices for their products in market m.

Note that firms observe fixed costs for all potential products when making their product decisions. However, the demand and marginal cost shocks $(\xi_{jmt}, \omega_{jmt})$ are realized after firms have chosen which products to sell. This timing assumption is the same as that in Eizenberg (2014), Wollmann (2018), and Fan and Yang (2020), but different from two recent papers on entry or product repositioning in the airline industry (Ciliberto, Murry and Tamer, 2021 and Li, Mazur, Park, Roberts, Sweeting and Zhang, 2022), which assume that firms observe demand and marginal cost shocks as well as fixed cost shocks when making entry decisions. In other words, they account for selection based on unobserved demand and marginal costs as well as on unobserved fixed cost shocks. By contrast, we allow for selection based only on unobserved fixed cost shocks and address selection based on unobservable demand and marginal cost shocks by including a large number of fixed effects in our demand and marginal cost functions. Specifically, we include product-, market-, and time-specific fixed effects. The remaining unobservables are month-to-month product/market-level transient shocks. We find it reasonable to assume that firms do not observe them when making product choices. We also show later that the estimated shocks play a small role in explaining demand and marginal costs.

Stage 2. Pricing In month t, firm n chooses prices p_{jmt} for all $j \in \mathcal{J}_{nm\tau}$ to maximize its variable profit:

$$\max_{p_{jmt}, j \in \mathcal{J}_{nm\tau}} \sum_{j \in \mathcal{J}_{nm\tau}} \left(p_{jmt} - mc_{jmt}\right) D_{jmt}\left(p_{jmt}, p_{-jmt}\right). \tag{9}$$

The marginal cost mc_{jmt} is decomposed into a product fixed effect FE_j^{mc}, a market fixed effect FE_m^{mc}, a month fixed effect FE_t^{mc}, the effect of facility-market distance γX_{jm} to account for any transportation cost, and a product-market-month specific shock ω_{jmt}:

$$mc_{jmt} = FE_j^{\text{mc}} + FE_m^{\text{mc}} + FE_t^{\text{mc}} + \gamma X_{jm} + \omega_{jmt}. \tag{10}$$

Note that this pricing model essentially assumes that the retail price of a product is the wholesale price plus a fixed markup by the distributor and the retailer. In fact, because we include product-, market-, and month-specific fixed effects in our specification of the brewery marginal cost, the markup can vary at the product, market, and month levels. We only need to assume that markups do not change in our counterfactual simulations.[15]

Stage 1. Entry and Product Decisions At the beginning of year τ, firm n is endowed with a set of potential products $\mathcal{J}_{n\tau}$ and decides on the set of products $\mathcal{J}_{nm\tau}$ to offer in market m. The profit-maximization problem at this stage is:

$$\max_{\mathcal{J}_{nm\tau} \subseteq \mathcal{J}_{n\tau}} \pi_{nm}\left(\mathcal{J}_{nm\tau}, \mathcal{J}_{-nm\tau}\right) - C_{nm}\left(\mathcal{J}_{nm\tau}\right), \tag{11}$$

where $\pi_{nm}\left(\mathcal{J}_{nm\tau}, \mathcal{J}_{-nm\tau}\right)$ is the expected variable profit and $C_{nm}\left(\mathcal{J}_{nm\tau}\right)$ is the fixed cost. We now derive the former and specify the latter.

To derive firm n's expected variable profit $\pi_{nm}\left(\mathcal{J}_{nm\tau}, \mathcal{J}_{-nm\tau}\right)$, we plug the second-stage equilibrium prices into its profit function, take the expectation over the transitory demand and marginal cost shocks, and sum over all months in a year. Formally, we use $\mathcal{J}_{-nm\tau}$ to denote the set of products that firm n's competitors sell in market m. Let $p_{jmt}\left(\mathcal{J}_{nm\tau}, \mathcal{J}_{-nm\tau}\right)$ and $Q_{jmt}\left(\mathcal{J}_{nm\tau}, \mathcal{J}_{-nm\tau}\right)$ denote the second-stage equilibrium price and quantity, respectively, which depend on the observable covariates $(\boldsymbol{x}_j,\ X_{jm})$, fixed effects $(FE_j^{\text{demand}},\ FE_m^{\text{demand}}, FE_t^{\text{demand}}, FE_j^{\text{mc}}, FE_m^{\text{mc}},\ FE_t^{\text{mc}})$ as well as the shocks $(\xi_{jmt}, \omega_{jmt})$ for all products in market m. Let $\xi_{mt} = \left(\xi_{jmt}, j \in \mathcal{J}_{nm\tau} \cup \mathcal{J}_{-nm\tau}\right)$ be the collection of demand shocks for all products in market m and define ω_{mt} for the marginal cost shocks analogously. Let $\mathcal{T}_\tau$ represent all months of year τ. Then, firm n's expected variable profit,

[15] Miller and Weinberg (2017) show that a double marginalization model where a brewery first sells to retailers does not significantly change their merger simulation results.

$\pi_{nm}\left(\mathcal{J}_{nm\tau}, \mathcal{J}_{-nm\tau}\right)$ in (11) is:

$$\begin{aligned}&\pi_{nm}\left(\mathcal{J}_{nm\tau}, \mathcal{J}_{-nm\tau}\right)\\ =&\sum_{t\in\mathcal{T}_\tau} E_{\xi_{mt},\omega_{mt}}\left(\sum_{j\in\mathcal{J}_{nm\tau}}\left[p_{jmt}\left(\mathcal{J}_{nm\tau}, \mathcal{J}_{-nm\tau}\right) - mc_{jmt}\right]\cdot Q_{jmt}\left(\mathcal{J}_{nm\tau}, \mathcal{J}_{-nm\tau}\right)\right). \end{aligned} \tag{12}$$

The fixed cost function in (11) is specified as

$$C_{nm}\left(\mathcal{J}_{nm\tau}\right) = \sum_{j\in\mathcal{J}_{nm\tau}}\left(W_{jm}\theta + \sigma_\zeta\zeta_{jm\tau}\right), \tag{13}$$

where W_{jm} is a vector of covariates including, for example, whether product j is a craft beer product. We assume the fixed cost shock $\zeta_{jm\tau}$ is i.i.d. and follows a standard normal distribution.

5 Estimation

5.1 Estimation of Demand Parameters and Marginal Costs

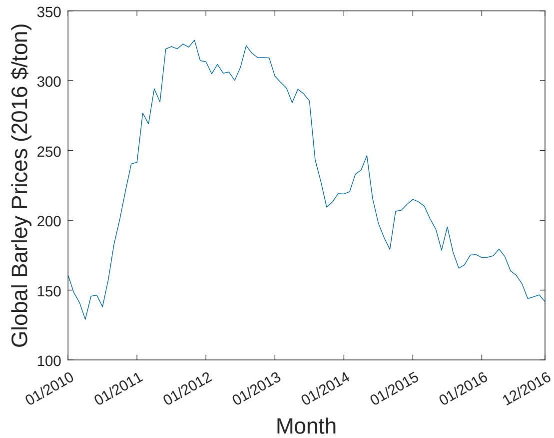
We combine the aggregate product/market/month-level data on prices, product characteristics, and market shares with the individual/month-level panel data on household purchases to estimate demand parameters. Specifically, we rely on the market share data to identify the mean taste coefficients (α, β) and fixed effects $(FE_j^{\text{demand}}, FE_m^{\text{demand}}, FE_t^{\text{demand}})$. We exploit the panel data and the correlations between household income and beer purchases to identify the standard deviations of the unobservable consumer heterogeneity (σ parameters) as well as the effect of household income on consumer tastes (κ parameters). We estimate these parameters using the Generalized Method of Moments approach, where we combine a set of macro moments with two sets of micro moments.

We construct macro moments based on instrumental variables consisting of the interactions of global barley prices with beer types to address potential price endogeneity. Barley is a common ingredient in almost all beers. Figure 2 plots the monthly price of barley in dollars per metric ton and shows fairly large monthly variations.[16]

We construct a new set of micro moments based on the persistence of a household's purchasing decisions to identify the standard deviation parameters. For example, a large value of σ^{craft} indicates that a household's preference for craft products is highly correlated across months. That means if a household ever purchases a craft product in a year, it

[16]Data source: https://fred.stlouisfed.org/series/PBARLUSDM

Figure 2: Price of Barley



is likely to purchase many craft products throughout the year. More generally, if we use $q^f_{i\tau} = \sum_{t \in \mathcal{T}_\tau} q^f_{it}$ to denote a household's purchase of beer type f ($f \in \{\text{ale}, \text{lager}, \ldots\}$) in year τ, then matching the conditional mean $E\left(q^f_{i\tau} \,|\, q^f_{i\tau} \geq 1\right)$ helps to identify the parameter σ^f.

Similar moments are also useful for identifying the correlation between taste shocks. For example, if a household that prefers type-f products tends to dislike type-f' products, then conditional on a household ever purchasing a type-f product, the household should buy few if any type-f' beers throughout the year.

Specifically, in constructing these micro moments, we match the model predictions of the following moments to their empirical counterparts (see Supplemental Appendix C for computational details):

- A household's expected annual purchase of a certain type of beer conditional on purchasing at least one unit of this type of beer in the year, i.e., $E\left(q^f_{i\tau} \,|\, q^f_{i\tau} \geq 1\right)$. Matching these moments helps to identify σ^f.

- A household's expected annual purchase of a certain type of beer conditional on purchasing at least one unit of craft beer in the year, i.e., $E\left(q^f_{i\tau} \,|\, q^{\text{craft}}_{i\tau} \geq 1\right)$. Matching these moments helps to identify the taste correlation between craft and type-f beer.

- A household's expected annual purchase of beer conditional on purchasing at least one unit of beer in the year, i.e., $E\left(q_{i\tau} \,|\, q_{i\tau} \geq 1\right)$, where $q_{i\tau}$ is a household's total beer purchase amount over a year. Matching this moment helps to identify σ_0.

We construct a second set of micro moments similar to those in Petrin (2002) to identify the effect of household income on consumer tastes:

- The ratio of average expenditure over average purchase quantity in a year among households whose income falls into a bin $\mathcal{I}$, i.e., $E\left(\text{expenditure}_{i\tau} \,|y_i \in \mathcal{I}\right) / E\left(q_{i\tau} \,|y_i \in \mathcal{I}\right)$, where the log-income bins $\mathcal{I}$ are $log\,(0, \$50K]$, $log\,(\$50K, \$100K]$, or $log\,(\$100K, +\infty)$.[17] Matching these moments helps to identify the income effect on price sensitivity, κ_1.

- $E\left(q_{i\tau}^{\text{craft}} \,|\, q_{i\tau}^{\text{craft}} \geq 1, y_i \in \mathcal{I}\right)$, which helps to identify κ^{craft}.
- $E\left(q_{i\tau} \,|\, q_{i\tau} \geq 1, y_i \in \mathcal{I}\right)$, which helps to identify κ_0.

Our estimation of marginal costs is standard and follows Berry, Levinsohn and Pakes (1995). Specifically, we back out marginal costs based on the first-order conditions of the profit maximization problem in equation (9).

5.2 Estimation of Fixed Cost Parameters

We follow the estimation procedure described in Section 2.2 to estimate the fixed cost parameters, which include the parameters of the mean fixed cost (θ) and the standard deviation of the fixed cost shock (σ_ζ).[18] In this section, we explain how we reformulate our empirical model to be consistent with the model outlined in Section 2.2, and importantly, present data patterns that help with identification. Estimation details are given in Supplemental Appendix D. We estimate the fixed cost parameters for each year separately and thus suppress the year subscript τ in this section for exposition simplicity.

Reformulation of the Model

To be consistent with the model outlined in Section 2.2, we rewrite the profit function in (11), i.e., $\pi_{nm}\left(\mathcal{J}_{nm}, \mathcal{J}_{-nm}\right) - \sum_{j\in\mathcal{J}_{nm}}\left(W_{jm}\theta + \sigma_\zeta\zeta_{jm}\right)$ as

$$\pi_n\left(Y_{nm}, Y_{-nm}, X_{nm}\right) - \sum_{j\in\mathcal{J}_n} Y_{jm}\left(W_{jm}\theta + \sigma_\zeta\zeta_{jm}\right). \tag{14}$$

Specifically, we now use a vector of indicators $Y_{nm} \in \{0,1\}^{\#\mathcal{J}_n}$ to denote a firm's product portfolio $\mathcal{J}_{nm} \subseteq \mathcal{J}_n$, where $\mathcal{J}_n$ represents the potential products that firm n is endowed with. We use Y_{jm} to denote the element of Y_{nm} that corresponds to product $j \in \mathcal{J}_n$, where $Y_{jm} = 1$ if $j \in \mathcal{J}_{nm}$ and 0 otherwise. Therefore, the expected variable profit $\pi_{nm}\left(\mathcal{J}_{nm}, \mathcal{J}_{-nm}\right)$ can be written as $\pi_n\left(Y_{nm}, Y_{-nm}, X_{nm}\right)$, where the vector X_{nm} includes all demand and marginal cost

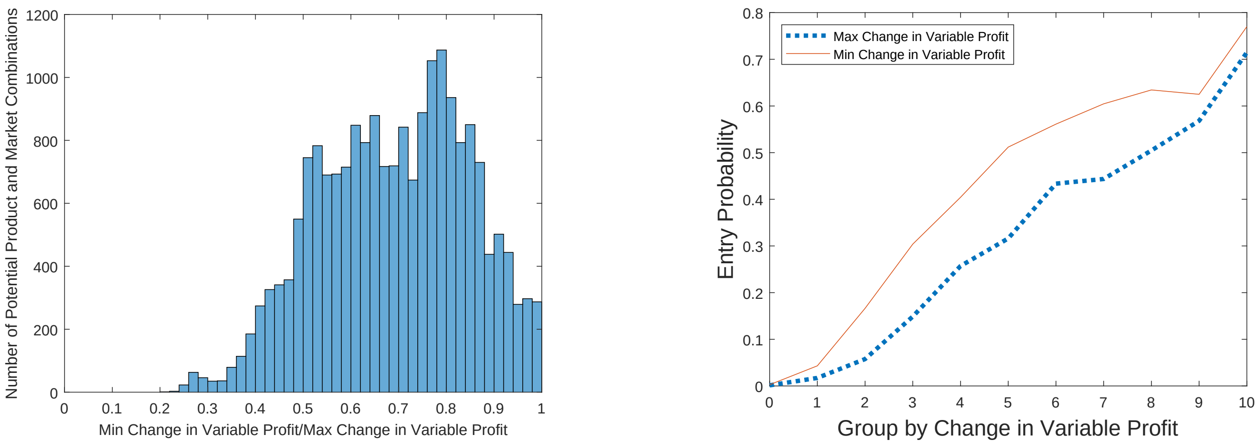
[17] An alternative moment is the average price $E\left(\frac{\text{expenditure}_{i\tau}}{q_{i\tau}} \,|\, y_i \in \mathcal{I}\right)$. However, computing this moment is more cumbersome. It requires drawing both v_i^f and ε_{ij} to simulate this moment but only v_i^f to simulate the moment in the text.

[18] Different from the model in Section 2.2, the variable profit function here is computed based on the estimated demand and marginal cost parameters. Therefore, we account for their estimation errors following the procedure explained in Supplemental Appendix B.

Figure 3: Data Patterns Aiding Identification

(A) Histogram of $\underline{\Delta}_j(X_{nm})/\overline{\Delta}_j(X_{nm})$

(B) Variations in $\underline{\Delta}_j(X_{nm}), \overline{\Delta}_j(X_{nm})$ and Entry Probability



covariates (including fixed effects). Similarly, the total fixed cost $\sum_{j\in\mathcal{J}_{nm}}(W_{jm}\theta+\sigma_\zeta\zeta_{jm})$ can be written as the summation over all products with $Y_{jm}=1$, i.e., $\sum_{j\in\mathcal{J}_n} Y_{jm}(W_{jm}\theta+\sigma_\zeta\zeta_{jm})$.

Data Patterns That Help with Identification

In Section 2, we discuss identification in abstract for a general model. Here, we present data patterns in our empirical setting that help with identification.

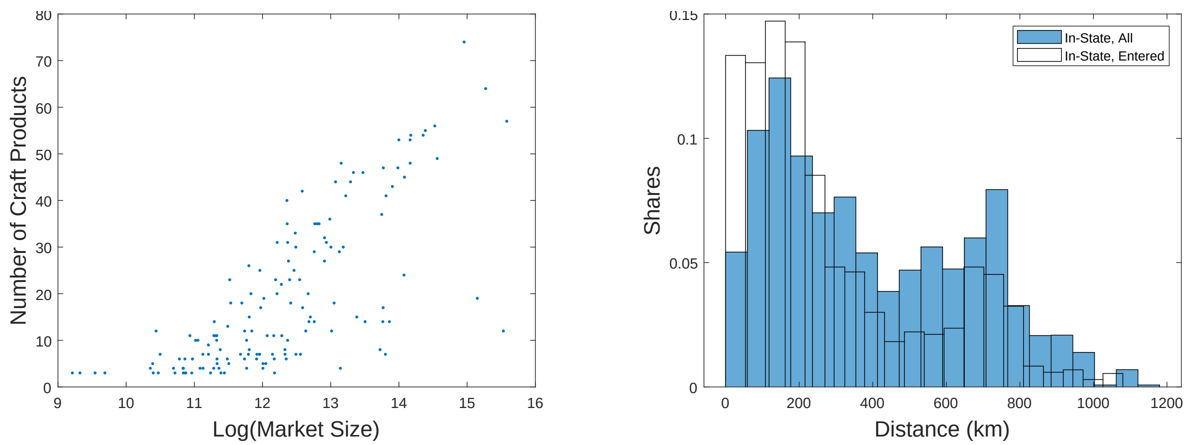
First, for a large proportion of the observations, the minimum and maximum changes in variable profit, i.e., $\underline{\Delta}_j(X_{nm})$ and $\overline{\Delta}_j(X_{nm})$, are relatively close, resulting in tight conditional choice probability bounds for these products. Panel (A) of Figure 3 plots the histogram of the ratio $\underline{\Delta}_j(X_{nm})/\overline{\Delta}_j(X_{nm})$ across all combinations of potential products and markets in 2016. The median of the ratio is around 0.7. In other words, for 50% of the observations, the ratio is larger than 0.7, where a larger ratio reflects a smaller difference between the minimum and maximum.

Second, there are considerable variations in $\underline{\Delta}_j(X_{nm})$ and $\overline{\Delta}_j(X_{nm})$, and these variations are informative about variations in entry probabilities. To see the variations in $\underline{\Delta}_j(X_{nm})$ and $\overline{\Delta}_j(X_{nm})$, we note that their 25%, 50%, and 75% percentiles are, respectively, (\$78.10, \$239.32, \$799.75) and (\$116.60, \$360.46, \$1187.09), where the 75% percentiles are more than 10 times of the 25% percentiles. To see the association between these variations and variations in entry probabilities, we discretize $\underline{\Delta}_j(X_{nm})$ into 10 groups. For each group g, we compute the average entry probability for observations jm such that $\underline{\Delta}_j(X_{nm})$ is in this group as $\dfrac{\sum_{j,m}\mathbb{1}\left(\underline{\Delta}_j(X_{nm})\in g\right)\cdot Y_{jm}}{\sum_{j,m}\mathbb{1}\left(\underline{\Delta}_j(X_{nm})\in g\right)}$, where $Y_{jm}\in\{0,1\}$ represents the observed entry out-

Figure 4: Exogenous Variations Aiding Identification

(A) Market Size and # Craft Products

(B) Distribution of Distance



come. We repeat this exercise for the association between entry probabilities and $\overline{\Delta}_j(X_{nm})$ analogously. Panel (B) of Figure 3 displays the average entry probabilities associated with $\underline{\Delta}_j(X_{nm})$ (represented by the red solid line) and those associated with $\overline{\Delta}_j(X_{nm})$ (represented by the blue dotted line). From the figure, we can see that the average entry probabilities increase in both $\underline{\Delta}_j(X_{nm})$ and $\overline{\Delta}_j(X_{nm})$.

What exogenous variations in X_{nm} generate the variations in $\underline{\Delta}_j(X_{nm})$ and $\overline{\Delta}_j(X_{nm})$? In addition to variations in product characteristics as well as the fixed effects in the demand and marginal cost functions, variations in market sizes also play an important role because everything else being equal, the returns to entry increase in the size of a market. This can be seen in Panel (A) of Figure 4, which depicts a strong positive correlation between the logarithm of market sizes and the number of craft products in a market.

Another source of exogenous variation is the distance between a production facility and a market. In Panel (B) of Figure 4, we plot the unconditional distribution of distances for all in-state craft potential product/market combinations and the conditional distribution for observed in-state craft product/market combinations (i.e., the product is in the market in the data).[19] Panel (B) shows that the conditional distribution has more probability mass at shorter distances than the unconditional one, suggesting a negative correlation between distance and entry. We account for these variations in variable profits by including controls for distances in both our demand and marginal cost functions.

[19]Out-of-state craft products tend to be widely distributed and thus less affected by the distance between their production facilities and markets. A number of such craft products in California are brewed on or near the East Coast.

Table 4: Demand Estimates

Unobserved	σ_0	0.00	Income Effect	κ_0	-2.15
Heterogeneity		(0.02)			(0.02)
	σ^{ale}	1.98		κ^{craft}	1.08
		(<0.01)			(0.02)
	σ^{lager}	0.89		κ_α	0.15
		(<0.01)			(<0.01)
	σ^{light}	2.67			
		(<0.01)	Price Coefficient	α	-2.26
	σ^{import}	2.14			(0.03)
		(<0.01)			
	σ^{craft}	2.44	Distance bin FE		Yes
		(<0.01)	Product FE		Yes
	$\rho^{\text{craft-light}}$	-0.28	Market FE		Yes
		(<0.01)	Time FE		Yes

Note: Standard errors are in parentheses.

6 Estimation Results

6.1 Demand and Markup

Table 4 reports the demand estimation results. The estimated σ parameters indicate significant heterogeneity in preferences for craft products, imported products, and flavor types. For example, the estimated standard deviation of the unobservable heterogeneity in consumer taste for craft products $\hat{\sigma}^{\text{craft}}$ is 2.44. To understand the magnitude of this estimate, we compare it to the price coefficient of a household with an income of \$50,000, which is $-2.26 + 0.15 \cdot log\,(\$50,000) = -0.64$. Therefore, the estimated $\hat{\sigma}^{\text{craft}}$ is equivalent to a price discount of 2.44/0.64, or 3.81 dollars.

The dispersion parameters $\sigma^{(\cdot)}$ are estimated by matching the micro moments that capture the persistence in a household's purchasing decisions. Table 5 shows the model fit for these micro moments. For example, from Row (6), we see that the average per-household annual craft purchase among households that purchase at least one unit of craft beers is 3.93. Compared with the unconditional average per-household annual craft purchase of 0.38 units, this micro moment implies that craft beers are purchased by a set of dedicated craft consumers, leading to a significant estimate of σ^{craft}.

The estimation results also indicate a negative correlation between consumer taste for craft and light beers ($\hat{\rho}^{\text{craft-light}} = -0.28$). This finding is consistent with the summary statistics in Table 3, which show that light craft beers account for only 0.44% of the craft beer sales while light beers in general account for 40% of all beer sales. We find that allowing for a

Table 5: Micro Moments on Persistence in Purchasing Decisions

		Data	Model
(1)	$E\left(\sum_{t=1}^{12} q_{it} \mid \sum_{t=1}^{12} q_{it} \geq 1\right)$	7.50	7.80
(2)	$E\left(\sum_{t=1}^{12} q_{it}^{\text{ale}} \mid \sum_{t=1}^{12} q_{it}^{\text{ale}} \geq 1\right)$	3.10	3.91
(3)	$E\left(\sum_{t=1}^{12} q_{it}^{\text{lager}} \mid \sum_{t=1}^{12} q_{it}^{\text{lager}} \geq 1\right)$	5.56	4.17
(4)	$E\left(\sum_{t=1}^{12} q_{it}^{\text{light}} \mid \sum_{t=1}^{12} q_{it}^{\text{light}} \geq 1\right)$	8.03	8.25
(5)	$E\left(\sum_{t=1}^{12} q_{it}^{\text{import}} \mid \sum_{t=1}^{12} q_{it}^{\text{import}} \geq 1\right)$	2.86	2.96
(6)	$E\left(\sum_{t=1}^{12} q_{it}^{\text{craft}} \mid \sum_{t=1}^{12} q_{it}^{\text{craft}} \geq 1\right)$	3.93	4.17

correlation between ν_i^{light} and ν_i^{craft} is helpful for matching the conditional purchases of light beers given at least one craft purchase. The moment $E\left(q_{i\tau}^{\text{light}} \mid q_{i\tau}^{\text{craft}} \geq 1\right)$ is 1.27 in the data and 1.07 according to our estimated model, and it would be 2.14 if such a correlation were not allowed in our model.

Moreover, we find heterogeneity in consumer tastes across income levels. Specifically, high-income households are less likely to purchase beer ($\hat{\kappa}_0 < 0$), have a stronger preference for craft products $\left(\hat{\kappa}^{\text{craft}} > 0\right)$, and are less price sensitive ($\hat{\kappa}_\alpha < 0$).

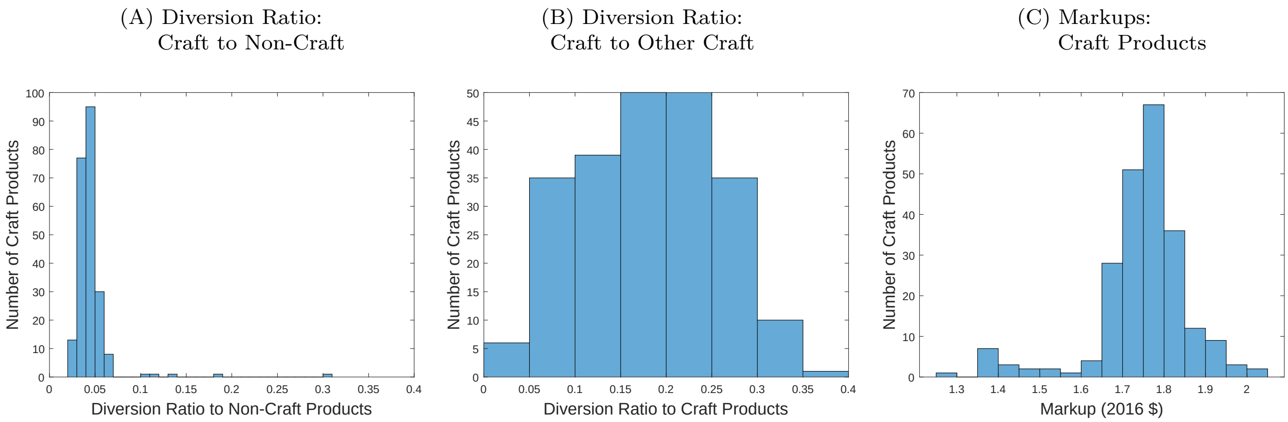
Overall, the estimated demand parameters imply that the substitution within craft products is much larger than the substitution between craft and non-craft products. Table 6 reports the own and cross elasticities among the top-3 non-craft and top-3 craft products in 2016.[20] These elasticities suggest little substitution between craft and non-craft products. Similarly, Figure 5 presents the histogram of the diversion ratio for a craft product to non-craft products (Panel (A)) and that for a craft product to other craft products (Panel (B)). Panel (A) shows that for most craft products, almost no sales would be captured by non-craft products if the focal craft product's price is increased. By contrast, the distribution of the diversion ratio to other craft products in Panel (B) has a mode of around 20%.

Table 6: Elasticities of Top-3 Craft Products and Top-3 Main Products (%)

	Craft			Main		
Craft	-10.09	0.14	0.02	0.01	0.01	0.01
	0.22	-9.52	0.02	0.01	0.01	0.01
	0.04	0.03	-9.16	0.01	0.03	0.01
Main	<0.01	<0.01	<0.01	-5.87	0.04	0.67
	<0.01	<0.01	<0.01	0.08	-6.81	0.08
	<0.01	<0.01	<0.01	0.68	0.04	-5.88

[20]Per our data agreement, we refrain from discussing the specific identities of beers or breweries in the data.

Figure 5: Histograms of Diversion Ratios and Markups



We back out the marginal costs using the first-order conditions at the pricing stage of the game and present the distribution of the quantity-weighted markup in Panel (C) of Figure 5. The median markup of craft beers is about $1.7 in 2016 dollars. Some industry sources (e.g., Satran, 2014) put the brewer's margin at 8% of the retail price, or $1.4 for an average price of $17, in line with our estimates.

Finally, we note that our observed explanatory variables account for the majority of the variations in demand and marginal costs. The R^2's from regressing the mean utility and marginal cost on observable covariates and fixed effects are both above 0.9, implying that after controlling for the product-, market-, and time-specific fixed effects, the month-to-month transient shocks $(\xi_{jmt}, \omega_{jmt})$ play, at most, a small role.

6.2 Fixed Costs

We estimate the fixed cost parameters year by year. In this section, we focus on craft products and present our fixed cost estimation results using the 2016 data for consistency with our later counterfactual analyses. In our estimation, one unit of observation is a potential product j and market m combination. In this part of the estimation, we exclude markets with no craft products, resulting in a total of 95 potential products, 149 markets, and 14,155 potential product/market combinations in 2016.

Table 7 reports the 95% confidence set projected to each parameter. These estimates account for the statistical errors in the estimation of the variable profits. We find a higher fixed cost for independent craft breweries and larger markets. The 95% confidence set projected to the coefficient of the craft indicator is [$128, $658], indicating that craft breweries incur higher fixed costs than non-craft breweries. This parameter is identified by the data

Table 7: Estimates of Fixed Costs: Projected 95% Confidence Intervals, 2016

Craft (θ_1)	[163.63, 276.68]
In State× Craft (θ_2)	[-77.54, 33.50]
Market-size specific fixed cost (θ_3)	
Small market	[631.37, 759.29]
Medium market	[822.40, 934.80]
Large market	[1902.60, 1998.82]
Market-size specific std. dev. (σ_ζ)	
Small market	[212.62, 321.91]
Medium market	[309.36, 414.19]
Large market	[878.99, 995.72]

Note: Estimates in 2016 US dollars.

pattern that products of craft breweries acquired by macro breweries are more likely to enter a market than those of independent craft breweries.[21] To study whether fixed costs vary with market size, we categorize markets into small, median, or large bins based on whether the market size is below 10^5, between 10^5 and $5{\times}10^5$, or above $5{\times}10^5$ units, and allow fixed costs to differ across bins.[22] We find that fixed costs are higher in larger markets and the standard deviation of the unobservable fixed cost shock also increases with market size.

7 Counterfactual Simulations

7.1 Counterfactual Designs

We consider a counterfactual merger where the largest firm in our sample, a so-called macro brewery, acquires the three largest craft firms in 2016, excluding the Boston Beer Company and the Sierra Nevada Brewing, which are unlikely merger targets given their sizes. In other words, we study a scenario where the trend of acquisitions in the craft beer industry continues to the point where the concentration of the craft market approaches the level in the overall beer market.[23]

[21] To clarify, for a craft product acquired by a macro brewery but still maintaining its craft status according to the Brewer Association's craft designation, we set its craft dummy to 0 in the fixed cost specification. This is because the product benefits from the distribution and marketing networks of the larger firms, which may affect its fixed costs.

[22] The 25% and 75% quantiles of the market sizes are $0.84{\times}10^5$ and $4.5{\times}10^5$ units.

[23] During our sample period, there are four observed acquisitions where a macro brewery acquired an independent craft brewery in our sample (and other mergers involving smaller craft breweries not in our sample). Of the four observed acquisitions, one brewery was not present in our sample prior to the transaction. Among the other three, we observe an increase in entry and product variety post-merger. Based on our estimated model, we simulate the outcome of a large acquisition in the year it occurred, allowing for fixed cost merger efficiency (see Section 7.2), and find that the simulated increase in product variety is consistent with data.

In our simulation, we allow firms to adjust their craft products and hold the non-craft product choices fixed as observed in the data (but allow their prices to change). Solving a product choice game is computationally challenging because each firm can choose any subset from its set of potential products and there are $2^{\#\text{ of potential products}}$ such subsets. We compute the post-merger product equilibrium using the algorithm outlined in Fan and Yang (2020).[24] We further ease the computational burden by holding the non-craft product choices fixed. This simplification is justified by the estimated small substitution between craft and non-craft products.

We consider a decision maker to be a firm that is observed in any market in our sample. Each firm is endowed with a set of potential products comprised of the firm's craft products observed in any market in the 2016 data. In each market, a firm chooses a subset from its potential products, and an empty subset denotes no entry. The potential product set for the merged firm consists of the combined set of potential products. We assume that firms maximize profits in both the product choice and pricing stages.

To quantify the effects of the merger and to decompose the overall effects into those due to price versus product variety adjustments, we conduct three counterfactual simulations. Specifically, in the counterfactual simulation described above (CF1), we allow for three adjustment margins — new entry, product adjustments, and price adjustments. In the second counterfactual (CF2), we allow for only incumbent product adjustment and price adjustment by removing the products added by new entrants in CF1 and recomputing the pricing equilibrium. In the third counterfactual (CF3), we allow for only the price effect of the merger by restoring pre-merger market products and recomputing the pricing equilibrium. The difference between the outcomes in CF1 and CF3 gives us the overall product variety effect of the merger, which can be further decomposed into the product variety effect due to new entry (CF1 - CF2) and that due to incumbent product adjustments (CF2 - CF3). For all simulations, we sample 30 vectors of parameter values from the 95% confidence set of our model parameters (i.e., the demand, marginal cost, and fixed cost parameters).

We draw three sets of shocks: demand, marginal cost, and fixed cost shocks. We draw demand and marginal cost shocks directly from their estimated distributions. For each sam-

[24] Fan and Yang (2020) develop a heuristic algorithm to find a firm's best-response product portfolio given the portfolios of its competitors, and embed this optimization algorithm in a best-response iteration to solve for the post-merger product-choice equilibrium. The algorithm starts with an initial vector of product decisions and evaluates whether adding or dropping a product is profitable. If a profitable deviation is found, the product vector is updated to the most profitable deviation among all such one-product deviation, and the process is repeated until no more profitable one-product deviations are possible. The algorithm is run with different initial vectors to check for multiple equilibria. We find identical results across two starting points, one based on the observed product decisions in the data and another where each firm chooses all potential products.

pled fixed cost parameter vector, we draw fixed cost shocks from the estimated distribution conditional on the observed pre-merger equilibrium to ensure that pre- and post-merger outcomes are comparable. Details on how we draw our fixed cost shocks can be found in Supplemental Appendix E.

For each sampled parameter vector, we compute the simulated merger effects averaged across the simulation draws of the demand, marginal cost, and fixed cost shocks. We report the range of this average effect across the sampled parameter vectors as the 95% confidence interval of the average effects.

7.2 Counterfactual Results

We present two sets of counterfactual simulation results, allowing for a merger efficiency in one and ignoring it in the other. A merger efficiency can arise because craft breweries could benefit from using the marketing networks of the acquirer and enjoy reduced fixed costs (Elzinga and McGlothlin, 2021).[25] According to our estimate of the parameter θ_1 in the fixed cost function, independent craft breweries face an extra fixed cost. Recall that this parameter is identified by the difference in product decisions between independent craft breweries and craft breweries acquired by the macro breweries, i.e., products by the latter breweries are more likely to enter a market. Therefore, to quantify the effects of a potential fixed cost reduction post-merger, we consider a scenario where the fixed costs of the acquired craft products decrease by the estimated θ_1, which is the extra fixed cost faced by independent craft breweries.

We report the merger effects on entry, product variety, and prices across markets without the merger efficiency in the left panels of Figure 6, those allowing for the merger efficiency in the right panels of Figure 6, and the aggregate welfare effects under both scenarios in Table 8. For the purpose of presentation, in Figure 6, instead of presenting the merger effects in each of the 149 markets separately, we sort markets into 10 groups according to market size from group 1 (smallest) to group 10 (largest). There are 15 markets in groups 1 to 9 and 14 largest markets in group 10. Within each group, we average counterfactual outcomes across markets weighted by their market size.

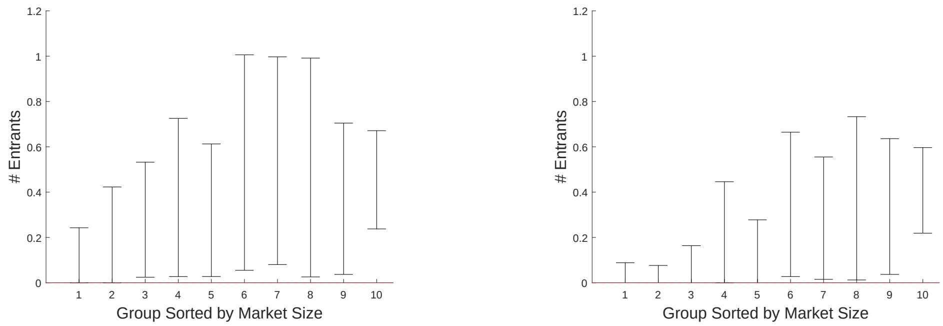
In the left panels of Figure 6, we show the merger effects on entry, product variety, and prices without considering the potential merger efficiency. We find that entry occurs in all market groups (Panel (A)). The number of added products by new entrants (Panel (B)) is

[25]Note that mergers involving craft breweries are unlikely to realize efficiency gains in marginal costs as craft breweries often remain operationally independent and their beers continue to be brewed at the same facilities in the short run. This arrangement stands in contrast to mergers among macro breweries, where the merged firms relocate production and economize on transportation costs from production facilities to markets (Ashenfelter, Hosken and Weinberg, 2015).

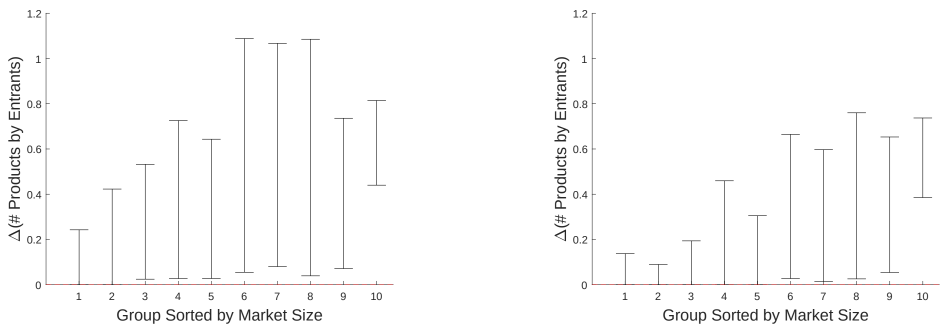
Figure 6: Merger Effects on Entry, Product Variety, and Prices

No Merger Efficiency | With Merger Efficiency

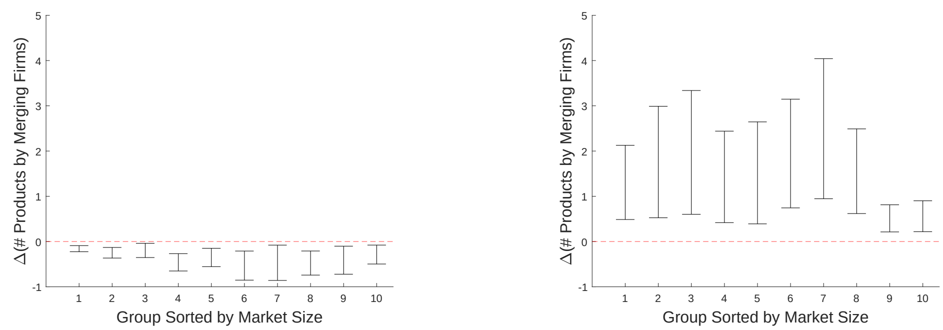
(A) Number of Entrants



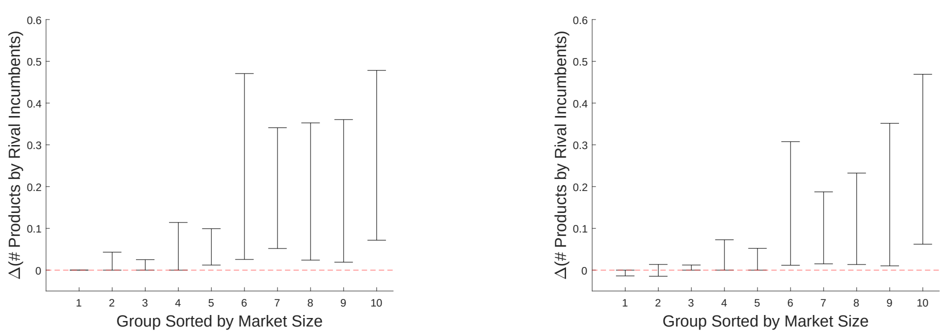
(B) Number of Products Added by Entrants



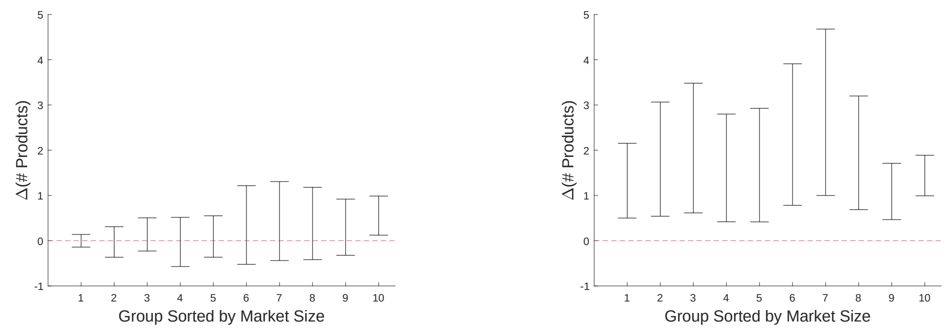
(C) Change in the Number of Products by Merging Firms



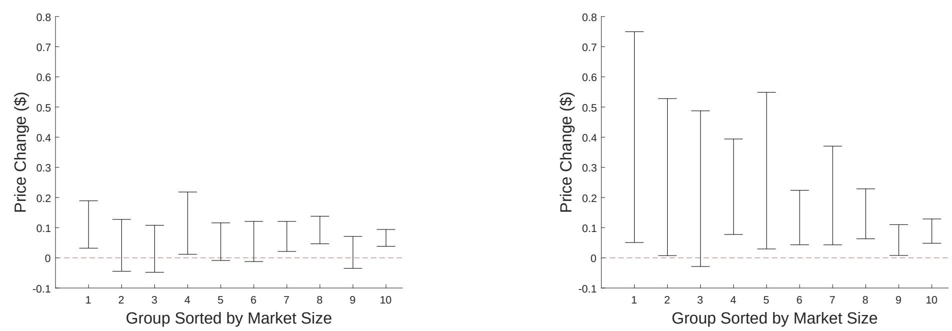
(D) Change in the Number of Products by Non-merging Incumbent Firms



(E) Change in the Number of Products



(F) Change in Craft Prices



almost identical to the number of new entrants, implying that new entrants, on average, enter with one product. As for incumbents, merging incumbents drop products (Panel (C)) while non-merging incumbents add products (Panel (D)). As a result, the change in the overall number of products is ambiguous (Panel (E)). The increase in the quantity-weighted average craft beer price (Panel (F)) is centered around 5 cents, but could be as large as nearly 20 cents, which is about 12% of the average markup.

The left panel of Table 8 reports the welfare effects of the merger ignoring the merger efficiency. It shows that consumers are worse off, with a decrease in consumer surplus of \$263,470 to \$842,620 (Row (1)). Row (3) shows that total surplus also decreases, but by a smaller amount due to the producer surplus gain. Our decomposition of the consumer surplus change shows that the effect of product variety change on consumer surplus is ambiguous (Row (4)). A further decomposition indicates that new entries recover the consumer welfare loss by \$23,330 to \$235,940 (Row (5)). The welfare effects of incumbent product adjustments are ambiguous (Row (6)), which is consistent with Figure 6 where merging incumbents drop products while non-merging incumbents add products.

Overall, in the scenario where the merger efficiency gain is ignored, new entries occur and these new entrants bring new products to markets after the merger. Non-merging incumbents also add products. However, their positive effects are not enough to offset the

Table 8: Welfare Effects

		No Merger Efficiency	With Merger Efficiency
(1)	consumer surplus ($1000)	[-842.62, -263.47]	[-591.56, -103.63]
(2)	craft beer profits ($1000)	[35.56, 174.94]	[32.29, 178.38]
(3)	total surplus ($1000)	[-698.81, -227.33]	[-436.78, -64.08]
ΔCS decomposition ($1000)			
(4)	due to variety change	[-34.52, 270.51]	[60.06, 565.99]
(5)	due to entry	[23.33, 235.94]	[18.59, 162.60]
(6)	due to incumbent product adjustments	[-57.85, 40.86]	[41.47, 416.05]

Note: this table reports the aggregate welfare effects of the merger across markets. For each measure, we report the range across the vectors of parameters sampled from their 95% confidence set. The left panel shows the results without considering any merger efficiency, while the right panel reports the results that incorporate reductions in fixed costs when a craft brewery is acquired by a macro brewery.

negative welfare effects from the merged firm dropping products and the increased prices.

We now turn to simulations allowing for the merger efficiency in reducing fixed costs. The right panels of Figure 6 demonstrate that the merging firms now add products (Panel (C)). At the same time, the number of new entrants becomes slightly smaller (Panel (A)) and so does the number of added products by new entrants (Panel (B)). Similarly, the change in the number of products by non-merging firms also becomes smaller or even negative in very small markets (Panel (D)). However, the overall number of products now increases (Panel (E)). At the same time, the upper bound of price changes become larger, indicating that prices could increase by a bigger margin (Panel (F)).

The results of simulations allowing for the merger efficiency show a reduction in the total consumer welfare loss, but not to the extent of reversing it. The range of loss is now between $103,630 to $591,560, according to the right panel of Row (1) in Table 8. Both new entries and product adjustment by incumbents help to alleviate the negative welfare effect, as shown in Rows (5) and (6), leading to a positive consumer welfare effect due to changes in product variety (Row (4)). Despite this, both the overall consumer surplus change and the total surplus change are still negative.

Note that efficiency gains associated with fixed costs can have countervailing effects on the number of products in a market. On the one hand, they can induce new product entry by merging firms. On the other hand, they can discourage product entry by new entrants and non-merging incumbents, limiting the overall positive effect of efficiency gains on product variety and consumer welfare. The latter countervailing effect exists because while prices are often strategic complements, product offerings tend to be strategic substitutes.

In sum, the merger results in new firm entries as well as product entries by non-merging incumbents in both scenarios, with more significant effects in larger markets. The effect on product variety depends on whether there is a merger efficiency in reducing fixed costs, and the merged firm may drop or add products accordingly. However, in both scenarios, the merger leads to a decrease in consumer surplus and total surplus.

8 Robustness Analyses

We conduct two robustness analyses. In the first robustness analysis, we extend our model and estimation method to allow for (dis)economies of scope in fixed costs. Our baseline model assumes additive separability of fixed costs across products, a common assumption in the literature of estimating discrete games. To estimate additional parameters governing (dis)economies of scope, we derive a new set of inequalities bounding the entry probability of a firm in addition to that of a product. We find that the merger simulation results based on the extended model remain robust. In the second robustness analysis, we consider an extension allowing for unobservable fixed cost shocks to be correlated. Specifically, we allow for a market-level unobservable shock that is common for all firms and products in a market. To estimate the standard deviation of this common shock, we additionally consider bounds for the joint probability of two products entering. We find a fairly modest standard deviation for this common shock and that our results are robust. Additional details on the extended models, updated estimation method, and results for these two robustness analyses can be found in Supplemental Appendices F and G, respectively.

9 Conclusion

We propose a new method to estimate discrete games and apply it to study merger effects on firm entry, product choice, and prices in the California retail craft beer market. The paper makes two contributions. Methodologically, we present a method to estimate discrete games that is easy to compute and scalable to games with many firms or many firm decisions. Empirically, the paper adds to the literature on merger, entry, and product variety with a joint study of merger effects on firm entry, product variety, and prices. We consider the simulation of a merger that could significantly increase the concentration of the craft beer market. We find that whether the merger leads to more or less product variety depends on whether a merger efficiency in reducing fixed costs is considered. We also find that new entries always occur after such a merger. However, even in our entry-favorable setting, the impact of new entries is insufficient to offset the overall negative effect of the merger. A merger efficiency in reducing fixed costs can only reduce, but not reverse, the consumer surplus loss.

References

Anderson, Simon, Nisvan Erkal, and Daniel Piccinin (2020), "Aggregative games and oligopoly theory: Short-run and long-run analysis." *The RAND Journal of Economics*, 51, 470–495.

Andrews, Donald WK and Xiaoxia Shi (2013), "Inference based on conditional moment inequalities." *Econometrica*, 81, 609–666.

Andrews, Donald WK and Gustavo Soares (2010), "Inference for parameters defined by moment inequalities using generalized moment selection." *Econometrica*, 78, 119–157.

Aradillas-Lopez, Andres and Elie Tamer (2008), "The identification power of equilibrium in simple games." *Journal of Business & Economic Statistics*, 26, 261–283.

Ashenfelter, Orley, Daniel Hosken, and Matthew Weinberg (2015), "Efficiencies brewed: Pricing and consolidation in the US beer industry." *The RAND Journal of Economics*, 46, 328–361.

Asker, John (2016), "Diagnosing foreclosure due to exclusive dealing." *The Journal of Industrial Economics*, 64, 375–410.

Beresteanu, Arie, Ilya Molchanov, and Francesca Molinari (2011), "Sharp identification regions in models with convex moment predictions." *Econometrica*, 79, 1785–1821.

Berry, Steven (1992), "Estimation of a model of entry in the airline industry." *Econometrica*, 60, 889–917.

Berry, Steven, Alon Eizenberg, and Joel Waldfogel (2016), "Optimal product variety in radio markets." *The RAND Journal of Economics*, 47, 463–497.

Berry, Steven, James Levinsohn, and Ariel Pakes (1995), "Automobile prices in market equilibrium." *Econometrica*, 63, 841–890.

Berry, Steven and Joel Waldfogel (2001), "Do mergers increase product variety? Evidence from radio broadcasting." *The Quarterly Journal of Economics*, 116, 1009–1025.

Bresnahan, Timothy and Peter Reiss (1991), "Entry and competition in concentrated markets." *Journal of political economy*, 99, 977–1009.

Bronnenberg, Bart, Jean-Pierre Dubé, and Joonhwi Joo (2022), "Millennials and the takeoff of craft brands: Preference formation in the US beer industry." *Marketing Science*, 41, 710–732.

Cabral, Luıs (2003), “Horizontal mergers with free-entry: Why cost efficiencies may be a weak defense and asset sales a poor remedy.” *International Journal of Industrial Organization*, 21, 607–623.

Caradonna, Peter, Nathan Miller, and Gloria Sheu (2021), “Mergers, entry, and consumer welfare.” *Georgetown McDonough School of Business Research Paper*.

Chernozhukov, Victor, Denis Chetverikov, and Kengo Kato (2019), “Inference on causal and structural parameters using many moment inequalities.” *The Review of Economic Studies*, 86, 1867–1900.

Chesher, Andrew and Adam M Rosen (2017), “Generalized instrumental variable models.” *Econometrica*, 85, 959–989.

Ciliberto, Federico, Charles Murry, and Elie Tamer (2021), “Market structure and competition in airline markets.” *Journal of Political Economy*, 129, 2995–3038.

Ciliberto, Federico and Elie Tamer (2009), “Market structure and multiple equilibria in airline markets.” *Econometrica*, 77, 1791–1828.

Codog, Aric (2018), “The antitrust roadblock: Preventing consolidation of the craft beer market.” *University of the Pacific Law Review*, 50, 403.

Croxall, Daniel (2019), “Helping craft beer maintain and grow market shares with private enforcement of tied-house and false advertising laws.” *Gonzaga Law Review*, 55, 167.

Draganska, Michaela, Michael Mazzeo, and Katja Seim (2009), “Beyond plain vanilla: Modeling joint product assortment and pricing decisions.” *QME*, 7, 105–146.

Eizenberg, Alon (2014), “Upstream innovation and product variety in the US home PC market.” *Review of Economic Studies*, 81, 1003–1045.

Elliott, Jonathan, Georges Vivien Houngbonon, Marc Ivaldi, and Paul Scott (2021), “Market structure, investment and technical efficiencies in mobile telecommunications.”

Elzinga, Kenneth G and Alexander J McGlothlin (2021), “Has Anheuser-Busch let the steam out of craft beer? The economics of acquiring craft brewers.” *Review of Industrial Organization*, 1–27.

Fan, Ying (2013), “Ownership consolidation and product characteristics: A study of the US daily newspaper market.” *American Economic Review*, 103, 1598–1628.

Fan, Ying and Chenyu Yang (2020), "Competition, product proliferation, and welfare: A study of the US smartphone market." *American Economic Journal: Microeconomics*, 12, 99–134.

Galichon, Alfred and Marc Henry (2011), "Set identification in models with multiple equilibria." *The Review of Economic Studies*, 78, 1264–1298.

Gandhi, Amit, Luke Froeb, Steven Tschantz, and Gregory Werden (2008), "Post-merger product repositioning." *The Journal of Industrial Economics*, 56, 49–67.

Garrido, Francisco Andres (2020), "Mergers between multi-product firms with endogenous variety: Theory and an application to the ready-to-eat cereal industry." working paper, ITAM.

Ho, Katherine (2009), "Insurer-provider networks in the medical care market." *American Economic Review*, 99, 393–430.

Huang, Yufeng, Paul B Ellickson, and Mitchell J Lovett (2022), "Learning to set prices." *Journal of Marketing Research*, 59, 411–434.

Illanes, Gastón (2017), "Switching costs in pension plan choice." *Unpublished manuscript*.

Illanes, Gastón and Sarah Moshary (2020), "Market structure and product assortment: Evidence from a natural experiment in liquor licensure." working paper 27016, National Bureau of Economic Research.

Jeziorski, Przemysław (2015), "Empirical model of dynamic merger enforcement–choosing ownership caps in US radio." working paper, University of California, Berkeley.

Lewbel, Arthur (2019), "The identification zoo: Meanings of identification in econometrics." *Journal of Economic Literature*, 57, 835–903.

Li, Sophia, Joe Mazur, Yongjoon Park, James Roberts, Andrew Sweeting, and Jun Zhang (2022), "Repositioning and market power after airline mergers." *The RAND Journal of Economics*, 53, 166–199.

McFadden, Daniel (1989), "A method of simulated moments for estimation of discrete response models without numerical integration." *Econometrica*, 57, 995–1026.

Miller, Nathan and Matthew Weinberg (2017), "Understanding the price effects of the MillerCoors joint venture." *Econometrica*, 85, 1763–1791.

Miller, Nathan H, Gloria Sheu, and Matthew C Weinberg (2021), "Oligopolistic price leadership and mergers: The United States beer industry." *American Economic Review*, 111, 3123–3159.

Pakes, Ariel, Jack Porter, Kate Ho, and Joy Ishii (2015), "Moment inequalities and their application." *Econometrica*, 83, 315–334.

Petrin, Amil (2002), "Quantifying the benefits of new products: The case of the minivan." *Journal of Political Economy*, 110, 705–729.

Reiss, Peter and Pablo Spiller (1989), "Competition and entry in small airline markets." *The Journal of Law and Economics*, 32, S179–S202.

Satran, Joe (2014), "Here's how a six-pack of craft beer ends up costing $12." *https://www.huffpost.com/entry/craft-beer-expensive-cost_n_5670015*.

Schennach, Susanne (2014), "Entropic latent variable integration via simulation." *Econometrica*, 82, 345–385.

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

Spector, David (2003), "Horizontal mergers, entry, and efficiency defences." *International Journal of Industrial Organization*, 21, 1591–1600.

Sweeting, Andrew (2010), "The effects of mergers on product positioning: Evidence from the music radio industry." *The RAND Journal of Economics*, 41, 372–397.

Sweeting, Andrew (2013), "Dynamic product positioning in differentiated product markets: The effect of fees for musical performance rights on the commercial radio industry." *Econometrica*, 81, 1763–1803.

Tamayo, Andrew (2009), "What's brewing in the old north state: An analysis of the beer distribution laws regulating North Carolina's craft breweries." *NCL Rev.*, 88, 2198.

Tamer, Elie (2003), "Incomplete simultaneous discrete response model with multiple equilibria." *The Review of Economic Studies*, 70, 147–165.

Tremblay, Victor J, Natsuko Iwasaki, and Carol Horton Tremblay (2005), "The dynamics of industry concentration for US micro and macro brewers." *Review of Industrial Organization*, 26, 307–324.

Wang, Shuang (2020), "Price competition with endogenous entry: The effects of Marriott & Starwood merger in Texas." working paper.

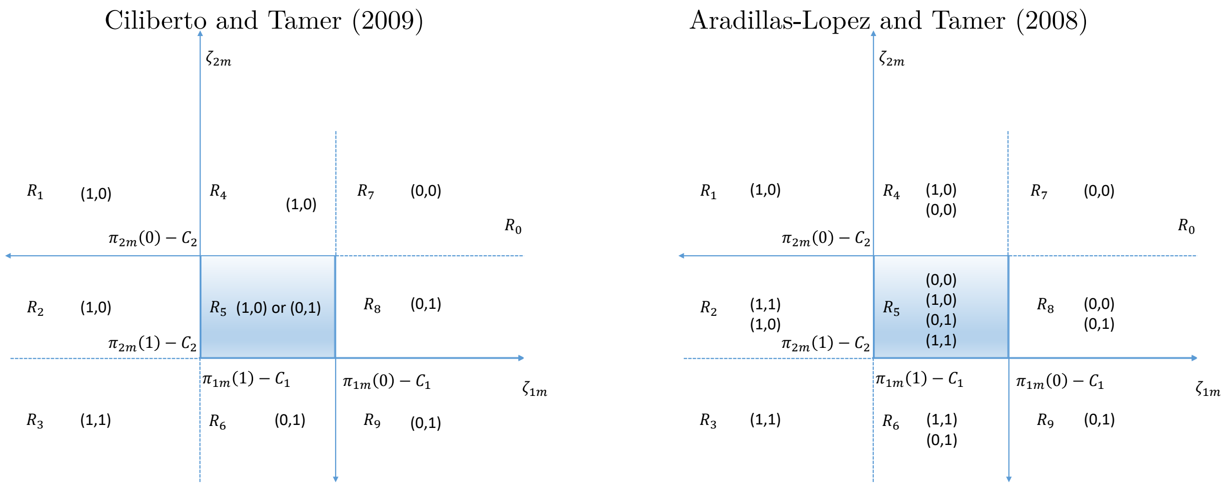
Watson, Bart (2016), "On-premise beer data and craft." *https://www.brewersassociation.org/insights/importance-on-premise-craft-brewers/*.

Werden, Gregory and Luke Froeb (1998), "The entry-inducing effects of horizontal mergers: An exploratory analysis." *The Journal of Industrial Economics*, 46, 525–543.

Wollmann, Thomas (2018), "Trucks without bailouts: Equilibrium product characteristics for commercial vehicles." *American Economic Review*, 108, 1364–1406.

A A Graphic Illustration of the Comparison of Our Bounds to the CT and the AT Bounds

Figure A.1: Model Implications Under Different Assumptions



The left graph of Figure A.1 lists all possible pure-strategy Nash equilibria in each region of (ζ_{1m}, ζ_{2m}) in the 2×2 entry game. We use $\Pr(R)$ to represent the probability that (ζ_{1m}, ζ_{2m}) is in region R. The Ciliberto and Tamer (2009) (henceforth, CT) bounds for $(Y_{1m} = 1, Y_{2m} = 0)$ are:

$$\sum_{\ell=1,2,4} \Pr(R_\ell) \leq \Pr(Y_{1m} = 1, Y_{2m} = 0) \leq \sum_{\ell=1,2,4,5} \Pr(R_\ell). \tag{A.1}$$

The CT bounds for $(Y_{1m} = 1, Y_{2m} = 1)$ degenerate into an equation:

$$\Pr(Y_{1m} = 1, Y_{2m} = 1) = \Pr(R_3). \tag{A.2}$$

Therefore, the CT bounds imply the following bounds for $\Pr(Y_{1m} = 1)$:

$$\sum_{\ell=1}^{4} \Pr(R_\ell) \leq \Pr(Y_{1m} = 1) \leq \sum_{\ell=1}^{5} \Pr(R_\ell). \tag{A.3}$$

By contrast, our bounds are

$$\sum_{\ell=1}^{3} \Pr(R_\ell) \leq \Pr(Y_{1m} = 1) \leq \sum_{\ell=1}^{6} \Pr(R_\ell). \tag{A.4}$$

These bounds are wider than those in (A.3).

The right panel of Figure A.1 shows all outcomes consistent with the level-1 rationality assumption. The Aradillas-Lopez and Tamer (2008) (henceforth, AT) bounds for $(Y_{1m}=1, Y_{2m}=1)$ and $(Y_{1m}=1, Y_{2m}=0)$ are, respectively:

$$\begin{aligned} \Pr(R_3) &\leq \Pr(Y_{1m}=1, Y_{2m}=1) \leq \sum_{\ell=2,3,5,6} \Pr(R_\ell), \\ \Pr(R_1) &\leq \Pr(Y_{1m}=1, Y_{2m}=0) \leq \sum_{\ell=1,2,4,5} \Pr(R_\ell). \end{aligned} \tag{A.5}$$

Note that in the region R_2, although the model implication for (Y_{1m}, Y_{2m}) is not unique, firm 1 always chooses the dominant strategy $Y_{1m}=1$. The AT bounds do not exploit such uniqueness of a firm's action while our bounds do.

Another way to see why the AT bounds are not necessarily sharper than ours is as follows. Under different equilibrium selection rules for selecting an outcome in regions R_2,R_4, R_5, R_6, and R_8, $\Pr(Y_{1m}=1, Y_{2m}=1)$ and $\Pr(Y_{1m}=1, Y_{2m}=0)$ are different. The possible values for $\Pr(Y_{1m}=1, Y_{2m}=1)$ and $\Pr(Y_{1m}=1, Y_{2m}=0)$ are

$$\begin{aligned} \Pr(Y_{1m}=1, Y_{2m}=1) &= \Pr(R_3) + \sum_{l=2,5,6} \alpha_l \Pr(R_l), \\ \Pr(Y_{1m}=1, Y_{2m}=0) &= \Pr(R_1) + \sum_{l=2,4,5} \beta_l \Pr(R_l), \end{aligned}$$

where $\alpha_l \in [0,1]$ is the probability that $(Y_{1m}=1, Y_{2m}=1)$ is the selected in region l and $\beta_l \in [0,1]$ is the probability that $(Y_{1m}=1, Y_{2m}=0)$ is selected in region l. Since $(Y_{1m}=1, Y_{2m}=1)$ and $(Y_{1m}=1, Y_{2m}=0)$ are the only two possible outcomes in R_2, we have $\alpha_2+\beta_2=1$. Similarly, we have $\alpha_5+\beta_5 \leq 1$.

The AT lower and upper bounds for $\Pr(Y_{1m}=1, Y_{2m}=1)$ in (A.5) are essentially

$$\min_{\{\alpha_2,\alpha_5,\alpha_6\}\in[0,1]^3} \Pr(R_3) + \sum_{l=2,5,6} \alpha_l \Pr(R_l) \quad \text{and} \quad \max_{\{\alpha_2,\alpha_5,\alpha_6\}\in[0,1]^3} \Pr(R_3) + \sum_{l=2,5,6} \alpha_l \Pr(R_l),$$

and those for $\Pr(Y_{1m}=1, Y_{2m}=0)$ are

$$\min_{\{\beta_2,\beta_4,\beta_5\}\in[0,1]^3} \Pr(R_1) + \sum_{l=2,4,5} \beta_l \Pr(R_l) \quad \text{and} \quad \max_{\{\beta_2,\beta_4,\beta_5\}\in[0,1]^3} \Pr(R_1) + \sum_{l=2,4,5} \beta_l \Pr(R_l).$$

In other words, the AT bounds only require α_l and β_l to be between 0 and 1, but ignore the requirement that $\alpha_2+\beta_2=1$. Below we show that our bounds use this condition.

Specifically, $\Pr(Y_{1m}=1)$ is

$$\Pr(R_1)+\Pr(R_3)+\sum_{l=2,5,6}\alpha_l \Pr(R_l)+\sum_{l=2,4,5}\beta_l \Pr(R_l).$$

Since $\alpha_2+\beta_2=1$, it can rewritten as

$$\Pr(R_1)+\Pr(R_2)+\Pr(R_3)+\sum_{l=5,6}\alpha_l \Pr(R_l)+\sum_{l=4,5}\beta_l \Pr(R_l).$$

Therefore, the minimum possible value for $\Pr(Y_{1m}=1)$ is $\Pr(R_1)+\Pr(R_2)+\Pr(R_3)$, which is our lower bound for $\Pr(Y_{1m}=1)$.

In sum, both our bounds and the CT and AT bounds exploit only a subset of conditions implied by a model. Different from the comparison between our bounds and the CT bounds, where one can see that the CT bounds exploit more model implications than our bounds, the model implications used in the AT bounds and our bounds do not nest each other.

B Details on Inference

This section provides details on how we construct the confidence set for the fixed-cost parameters based on the inequalities in (7).

Following the literature on inference based on conditional moment inequalities, we transform the conditional moment inequalities in (7) into unconditional ones:

$$\begin{aligned}
E\left(\frac{1}{\#\mathcal{J}}\sum_{j\in\mathcal{J}} L\left(Y_{jm},X_{nm},W_{jm},\theta,\sigma_\zeta\right)\cdot g^{(k)}\left(X_{nm},W_{jm}\right)\right) &\leq 0, \\
E\left(\frac{1}{\#\mathcal{J}}\sum_{j\in\mathcal{J}} H\left(Y_{jm},X_{nm},W_{jm},\theta,\sigma_\zeta\right)\cdot g^{(k)}\left(X_{nm},W_{jm}\right)\right) &\leq 0,
\end{aligned} \tag{B.1}$$

where $g^{(k)}, k=1,...,K$ are non-negative functions of (X_{nm},W_{jm}) that capture the information contained within the conditioning variables.[26] Note that even under the independence assumption related to the fixed cost shock ζ_{jm} across j, Y_{jm} across j within the same market m may be correlated due to strategic interdependence among firms. However, the entry decisions Y_{jm} are independent across markets. In (B.1), we average over potential products and exploit variations across markets.[27]

[26] We describe the g functions in Supplemental Appendix D.

[27] While intuitive, averaging over potential products is not strictly necessary. One could account for the correlation among observations indexed by jm and adjust the estimate of the covariance matrix of the moments accordingly.

We construct our confidence set by inverting the test in Andrews and Soares (2010).[28] With an abuse of notation, we now use θ to denote the fixed cost parameters including both the coefficients of covariates (originally denoted by θ) and the parameters in the distribution of the unobservable fixed cost shock (originally denoted by σ_ζ). We also denote the moment functions in (7) by $Z_{m,\tilde{k}}(\theta)$, $\tilde{k} = 1, \ldots, 2K$. For the first K moment functions, $Z_{m,\tilde{k}}(\theta)$ corresponds to $\frac{1}{\#\mathcal{J}} \sum_{j \in \mathcal{J}} L(Y_{jm}, X_{nm}, W_{jm}, \theta, \sigma_\zeta) \cdot g^{(k)}(X_{nm}, W_{jm})$ in (7). For $\tilde{k} = K + 1, \ldots, 2K$, $Z_{m,\tilde{k}}(\theta)$ corresponds to $\frac{1}{\#\mathcal{J}} \sum_{j \in \mathcal{J}} H(Y_{jm}, X_{nm}, W_{jm}, \theta, \sigma_\zeta) \cdot g^{(k)}(X_{nm}, W_{jm})$ in (7).

The sample moment functions are

$$\bar{Z}_M(\theta) = (\bar{Z}_{M,1}(\theta), ..., \bar{Z}_{M,2K}(\theta))',$$

where

$$\bar{Z}_{M,\tilde{k}}(\theta) = \frac{1}{M} \sum_{m=1}^{M} Z_{m,\tilde{k}}(\theta).$$

Let

$$\hat{\Sigma}_M(\theta) = \frac{1}{M} \sum_{m=1}^{M} \left(Z_m(\theta) - \bar{Z}_M(\theta)\right) \left(Z_m(\theta) - \bar{Z}_M(\theta)\right)'$$

be the estimator of the covariance matrix of $\sqrt{M}\bar{Z}_M(\theta)$.

The test statistic is given by

$$T_M(\theta) = S(\sqrt{M}\bar{Z}_M(\theta), \hat{\Sigma}_M(\theta)),$$

where

$$S(Z, \Sigma) = \sum_{\tilde{k}=1}^{2K} [Z_{\tilde{k}}/\sigma_{\tilde{k}}]_+^2$$

is the modified method of method test function, $\sigma_{\tilde{k}}^2$ is the $\tilde{k}$th diagonal element of Σ, and the function $[\cdot]_+$ takes the value of the argument if it is positive and 0 otherwise.

The critical value for the null hypothesis $H_0 : \theta = \theta_0$, denoted by $\hat{c}_M(\theta_0, 1 - \alpha)$, is the $(1 - \alpha)$th quantile of $S(\hat{\Omega}_M^{1/2}(\theta_0)R + [\eta_M(\theta_0)]_-, \hat{\Omega}_M(\theta_0))$, where $R \sim N(0_{2K}, I_{2K})$, $\hat{\Omega}_M(\theta) = \hat{D}_M^{-1/2}(\theta)\hat{\Sigma}_M(\theta)\hat{D}_M^{-1/2}(\theta)$, $\hat{D}_M(\theta) = Diag(\hat{\Sigma}_M(\theta))$, $\eta_M(\theta) = (lnM)^{-1/2}M^{1/2}\hat{D}_M^{-1/2}(\theta)$, and $[\eta_M(\theta)]_- = ([\eta_{M,1}(\theta)]_-, ..., [\eta_{M,2K}(\theta)]_-)$. In practice, following Andrews and Soares (2010), we simulate 500 draws of the $2K$-dimensional random vector R from the standard normal distribution to compute the critical value.

We invert this test to construct our confidence set. We consider a large set of parameter

[28]The estimator in Andrews and Soares (2010) has better power properties than using the approach in Andrews and Shi (2013) and Chernozhukov, Chetverikov and Kato (2019) in our Monte Carlo simulations. The comparison results are available upon request.

values and include a point θ_0 in the confidence set if $T_M(\theta_0) \leq \hat{c}_M(\theta_0, 1-\alpha)$. In practice, we use a three-step stochastic search process. In step 1, we find $\theta_0^\star$ that minimizes the test statistic $T_M(\theta)$. In step 2, we add to $\theta_0^\star$ a perturbation, which is drawn from an independent multivariate normal distribution with mean 0 and standard deviation $\frac{1}{5}$, and check whether the test statistic at the new point is below the corresponding critical value. If it is, we save the new point as $\theta_1^\star$ and perturb it. If not, we consider another perturbation to $\theta_0^\star$. We continue to add perturbations in this fashion 50 times. Then, we repeat this forward perturbation process 80 times and collect all points satisfying $T_M(\theta_0) \leq \hat{c}_M(\theta_0, 1-\alpha)$. In step 3, we select 160 points obtained from step 2 and for each one of them, we conduct a forward perturbation similar to the one in step 2, except that the perturbations are now drawn from a standard normal distribution (i.e., with a larger variance than the perturbation in step 2). The 160 selected points consist of two groups. To obtain the first group, we sample with replacement 80 times from the points at the boundary of the confidence set obtained in step 2, i.e., at least one dimension of these points is the maximum or minimum along that dimension among all points in the confidence set found in step 2. We do so to ensure that we consider points beyond the boundary of the confidence set in step 2. To obtain the second group of 80 points, we sample with replacement from the entire confidence set obtained in step 2. The confidence set is constructed as the union of all points in this three-step process whose test statistic value is below the corresponding critical value. This process yields a similar confidence set when we double the number of forward perturbations in steps 2 and 3 and the number of selected points in step 3.

In the empirical part of the paper, our moment functions are constructed based on the estimated demand and marginal cost parameters. When the moment functions depend on estimated parameters (that are estimated before estimating θ), the estimated covariance of the moments $\hat{\Sigma}_M(\theta)$ need to be adjusted to account for the estimation errors in these parameters. Specifically, we simulate $\hat{\Sigma}_M(\theta)$ from the asymptotic distribution of the demand and marginal cost parameters.

C Details on Micro Moments

In this section, we explain how we compute the model prediction for the micro moment $E\left(q_{i\tau}^{f'} \,|\, q_{i\tau}^{f} \geq 1\right)$. The calculation for other micro-moments in Section 5.1 is similar. In this moment, $q_{i\tau}^{f}$ is household i's quantity of beer of type f in year τ, and f' could be the same or a different type.

Let $s_{jmt}\left(\boldsymbol{\nu}, y\right)$ denote the Logit choice probability of product j in month t when the vector of unobserved tastes is $\boldsymbol{\nu}$ and log-income is y. Let $G_m\left(\boldsymbol{\nu}, y\right)$ denote the distribution of $\left(\boldsymbol{\nu}, y\right)$, which can vary across markets and is thus indexed by m. We assume that each consumer has 8 opportunities to buy beer per month, which is the average number of household trips per month in the Nielsen Consumer Panel data.[29] Then, the probability that a household with values $(\boldsymbol{\nu}, y)$ buys type-f products in market m in year τ is

$$\psi_{m\tau}^{f}\left(\boldsymbol{\nu}, y\right) = 1 - \prod_{t \in \mathcal{T}_{\tau}} \left(1 - \sum_{j \in \mathcal{J}_{m\tau}^{f}} s_{jmt}\left(\boldsymbol{\nu}, y\right)\right)^{8},$$

where $\mathcal{J}_{m\tau}^{f}$ is the collection of all type-f products in market m in year τ. The conditional expectation of the annual purchase of type-f' products for households in market m and year τ is, therefore,

$$E_{m\tau}\left(q_{i\tau}^{f'} \mid q_{i\tau}^{f} \geq 1\right) = \int_{\boldsymbol{\nu}, y} \frac{\sum_{t \in \mathcal{T}_{\tau}} \sum_{j \in \mathcal{J}_{m\tau}^{f'}} 8 \cdot s_{jmt}\left(\boldsymbol{\nu}, y\right)}{\psi_{m\tau}^{f}\left(\nu, y\right)} dG_{m}\left(\boldsymbol{\nu}, y\right),$$

where $E_{m\tau}$ is the expectation specific to a market m and a year τ. To obtain the average across market/year combinations, we weigh these conditional means in each market/year combination by the expected number of households who purchase type-f products, which is the product of the market size and the unconditional probability of purchasing type-f products in a market/year, i.e.,

$$weight_{m\tau} = MktSize_{m\tau} \cdot \int \psi_{m\tau}^{f}\left(\boldsymbol{\nu}, y\right) dG_{m}\left(\boldsymbol{\nu}, y\right).$$

Therefore, the expected purchase of type-f' products conditional on having at least one purchase of type-f products is

$$E\left(q_{i\tau}^{f'} \mid q_{i\tau}^{f} \geq 1\right) = \frac{\sum_{m\tau} E_{m\tau}\left(q_{i\tau}^{f'} \mid q_{i\tau}^{f} \geq 1\right) \cdot weight_{m\tau}}{\sum_{m\tau} weight_{m\tau}}.$$

D Details on the Fixed Cost Estimation

Approximate $\underline{\Delta}_{j}\left(X_{nm}\right)$ and $\overline{\Delta}_{j}\left(X_{nm}\right)$

To compute the moment functions, we need to compute $\underline{\Delta}_{j}\left(X_{nm}\right) = \min_{Y_{-jm}} \Delta_{j}(Y_{-jm}, X_{nm})$ and $\overline{\Delta}_{j}\left(X_{nm}\right) = \max_{Y_{-jm}} \Delta_{j}\left(Y_{-jm}, X_{nm}\right)$, where $\Delta_{j}\left(Y_{-jm}, X_{nm}\right)$ is the change in firm n's expected variable profit when product j joins the market, as defined in equation (4). Directly solving for the minimum and maximum of the expected profit across all possible values of

[29] The demand estimates are robust to $5, 6, 7$ opportunities of purchase per month.

Y_{-jm} may be computationally prohibitive because there are $2^{(\text{length of } Y_{-jm})}$ possible values of Y_{-jm} and for each value of Y_{-jm}, one needs to solve a pricing game for multiple simulated draws of demand and marginal cost shocks in order to compute $\Delta_j(Y_{-jm}, X_{nm})$. Economic intuition suggests that, because products are substitutes, we can approximate the minimum and maximum by, respectively, the following:

$$\underline{\Delta}_j(X_{nm}) \approx \Delta_j((1,...,1), X_{nm}) \text{ and } \overline{\Delta}_j(X_{nm}) \approx \Delta_j((0,...,0), X_{nm}).$$

These approximate extrema are exact for entry games such as those in Berry (1992), Seim (2006), Ciliberto and Tamer (2009), Sweeting (2013), and Berry, Eizenberg and Waldfogel (2016). For more general demand and pricing models such as ours, we find that the approximate extrema coincide with the true values in all of our computational experiments.[30]

Non-negative Functions

We define our non-negative functions $g^{(k)}(X_{nm}, W_{jm})$ in (B.1) as functions of $\underline{\Delta}_j(X_{nm})$, $\overline{\Delta}_j(X_{nm})$, and W_{jm}, where $\underline{\Delta}_j(X_{nm})$ and $\overline{\Delta}_j(X_{nm})$ are summary statistics of a long vector of covariates capturing market structure and the characteristics of each potential product, and the vector W_{jm} includes covariates in the fixed cost function. Among these variables, W_{jm} consists of indicator variables, but $\underline{\Delta}_j(X_{nm})$ and $\overline{\Delta}_j(X_{nm})$ are continuous variables. To define the functions $g^{(k)}(X_{nm}, W_{jm})$, we specify a series of cutoffs for $\underline{\Delta}_j(X_{nm})$ and $\overline{\Delta}_j(X_{nm})$, which are[31]

$$\{180, 360, 720, 960\}.$$

For each cutoff (denoted by b) and each dimension of W_{jm} (denoted by $W_{jm\lambda}$), we define the following functions:

$$\mathbb{1}\left(\overline{\Delta}_j(X_{nm}) \leq b\right) \cdot W_{jm\lambda},$$

$$\mathbb{1}\left(\underline{\Delta}_j(X_{nm}) \leq b \leq \overline{\Delta}_j(X_{nm})\right) \cdot W_{jm\lambda},$$

$$\mathbb{1}\left(\underline{\Delta}_j(X_{nm}) \geq b\right) \cdot W_{jm\lambda}.$$

We define another set of functions by replacing $W_{jm\lambda}$ in the above functions by $1 - W_{jm\lambda}$. Our non-negative functions $g^{(k)}(X_{nm}, W_{jm})$ include all these functions. Our results are robust to

[30] We randomly sample 100 markets and K potential products. For each selected potential product j in a selected market, we hold fixed the entry outcomes of the products not included in the K selected products, and go over all possible outcomes for the other $K-1$ products to find the actual extrema. For all sampled markets and K products when K takes the value of 6, 8, or 10, we find that the approximations coincide with the actual extrema.

[31] For our Monte Carlo simulations where $W_{jm} = 1$ and $\underline{\Delta}_j(X_{nm})$ and $\overline{\Delta}_j(X_{nm})$ are, respectively, $\pi_{nm}(1,\ldots,1)$ and $\pi_{nm}(0,\ldots,0)$, we use the cutoffs $\{0.125, 0.250, 0.500, 0.750, 0.875\}$.

using alternative cutoffs such as $\{180, 600, 960\}$ and $\{240, 420, 600, 780, 960\}$.

E Details on Fixed Cost Simulation Draws in Counterfactual Simulations

We draw fixed costs consistent with both the estimated distribution of fixed cost and the observed pre-merger outcome as an equilibrium. As explained in Section 7, it is important to take into account the requirement that fixed costs are consistent with the observed pre-merger outcome as an equilibrium, as this is essentially a selection issue. To obtain one such set of draws in a market m, we proceed with the following steps:

1. For each potential product j of firm n, we calculate the change in firm n's expected variable profit when product j enters the market, as defined in equation (4),

$$\mathit{\Delta}_j\left(Y_{-jm}, X_{nm}\right) = \pi_n\left(Y_{jm} = 1, Y_{-jm}, X_{nm}\right) - \pi_n\left(Y_{jm} = 0, Y_{-jm}, X_{nm}\right),$$

   where we plug in the observed Y_{-jm}. If product j is observed in market m, we define a range $(-\infty, \mathit{\Delta}_j\left(Y_{-jm}, X_{nm}\right))$. Otherwise, we define a range $(\mathit{\Delta}_j\left(Y_{-jm}, X_{nm}\right), \infty)$.

2. We simulate draws of the fixed costs for firm n from a truncated normal distribution with the underlying normal distribution parameterized by mean $W_{jm}\hat{\theta}$ and variance $\hat{\sigma}_{\zeta}^2$. The support of the truncated distribution is defined by the ranges in step 1. These draws satisfy the necessary conditions for the observed outcome to be an equilibrium.

3. For each draw from step 2, we check whether firm n's best response to Y_{-nm} is indeed Y_{nm}, where Y_{nm} and Y_{-nm}, respectively, represent firm n's and its opponents' product decisions in market m in the data. We find each firm's best response by employing the algorithm in Fan and Yang (2020) using two starting points, i.e., $Y_{nm}^0 = (0, ..., 0)$ and $Y_{nm}^0 = (1, ..., 1)$. If the algorithm converges to Y_{nm} from both starting points, we keep the set of draws for firm n. If at least one of the starting points does not lead to Y_{nm}, we go back to step 2 and re-draw the fixed costs.

4. We repeat this process for every firm n.

F Robustness Analysis: (Dis)Economies of Scope

In this section, we extend our model to allow for (dis)economies of scope in fixed costs and derive a new set of inequalities bounding the entry probability of a firm in addition to that of a product in order to estimate the additional parameter. We find economies of scope in the medium-sized markets. Our merger simulation results are, however, robust.

Our fixed cost specification in the paper is additively separable across products and, thus, does not allow for (dis)economies of scope. We consider the following extension of the fixed cost function:

$$\theta_0 \mathbb{1}\left(\sum_{j\in\mathcal{J}_n} Y_{jm} > 0\right) + \sum_{j\in\mathcal{J}_n} Y_{jm}\left(W_{jm}\theta + \sigma_\zeta \zeta_{jm}\right),$$

which is no longer additive in the fixed cost of each product. The fixed cost function exhibits economies (or diseconomies) of scope if $\theta_0 > 0$ (or $\theta_0 < 0$).

To estimate θ_0, we additionally consider bounds for the conditional probability that a firm has at least one product in a market, denoted by $\Pr(\sum_{j\in\mathcal{J}_n} Y_{jm} > 0 \,|\, X_{nm}, W_{nm})$, where $W_{nm} = (W_{jm}, j \in \mathcal{J}_n)$ is the collection of the fixed cost covariates for firm n's potential products. We define $\zeta_{nm} = (\zeta_{jm}, j \in \mathcal{J}_n)$ analogously. Also, let $Y_{nm} = (Y_{jm}, j \in \mathcal{J}_n)$ be firm n's product decision in market m and Y_{-nm} be the opponents' decisions. Finally, we denote firm n's maximum profit from entering the market for given $(Y_{-nm}, X_{nm}, W_{nm})$ by

$$\begin{aligned}
&\Gamma_{nm}(Y_{-nm}, X_{nm}, W_{nm}, \zeta_{nm}, \theta, \sigma_\zeta) \\
&= \max_{\{Y_{nm} \text{ s.t. } \sum_{j\in\mathcal{J}_n} Y_{jm} > 0\}} \pi_n(Y_{nm}, Y_{-nm}, X_{nm}) - \sum_{j\in\mathcal{J}_n} Y_{jm}\left(W_{jm}\theta + \sigma_\zeta \zeta_{jm}\right) - \theta_0.
\end{aligned}$$

We define the minimum

$$\underline{\Gamma}_{nm}(X_{nm}, W_{nm}, \zeta_{nm}, \theta, \sigma_\zeta) = \min_{Y_{-nm}} \Gamma_{nm}(Y_{-nm}, X_{nm}, W_{nm}, \zeta_{nm}, \theta, \sigma_\zeta)$$

and the maximum

$$\overline{\Gamma}_{nm}(X_{nm}, W_{nm}, \zeta_{nm}, \theta, \sigma_\zeta) = \max_{Y_{-nm}} \Gamma_{nm}(Y_{-nm}, X_{nm}, W_{nm}, \zeta_{nm}, \theta, \sigma_\zeta).$$

Under the assumption that the observed brewery entry decisions are not dominated, the bounds for $\Pr(\sum_{j\in\mathcal{J}_n} Y_{jm} > 0 \,|\, X_{nm}, W_{nm})$ are

$$\begin{aligned}
&\Pr\left(\underline{\Gamma}_{nm}\left(X_{nm}, W_{nm}, \zeta_{nm}, \theta, \sigma_\zeta\right) > 0\right) \\
&\leq \Pr\Big(\sum_{j\in\mathcal{J}_n} Y_{jm} > 0 \,|\, X_{nm}, W_{nm}\Big) \\
&\leq \Pr\left(\overline{\Gamma}_{nm}\left(X_{nm}, W_{nm}, \zeta_{nm}, \theta, \sigma_\zeta\right) > 0\right).
\end{aligned}$$

Unfortunately, computing $\Gamma_{nm}(Y_{-nm}, X_{nm}, W_{nm}, \zeta_{nm}, \theta, \sigma_\zeta)$ can be costly because there are many possible values for Y_{nm} in $\{Y_{nm} \text{ s.t. } \sum_{j\in\mathcal{J}_n} Y_{jm} > 0\}$. Consequently, computing its lower and upper bounds, $\underline{\Gamma}_{nm}\left(X_{nm}, W_{nm}, \zeta_{nm}, \theta, \sigma_\zeta\right)$ and $\overline{\Gamma}_{nm}\left(X_{nm}, W_{nm}, \zeta_{nm}, \theta, \sigma_\zeta\right)$, is also costly. In what follows, we define a function $\tilde{\underline{\Gamma}}_{nm}(\cdot)$ that is always smaller than or equal to $\underline{\Gamma}_{nm}(\cdot)$ and a function $\tilde{\overline{\Gamma}}_{nm}(\cdot)$ that is always larger than or equal to $\overline{\Gamma}_{nm}(\cdot)$, and use these functions to construct the bounds for $\Pr(\sum_{j\in\mathcal{J}_n} Y_{jm} > 0 \,|X_{nm}, W_{nm})$.

We start by noting that $\pi_n((1,1,0), Y_{-nm}, X_{nm})$ can be written as the sum of two differences: $\pi_n((1,1,0), Y_{-nm}, X_{nm}) - \pi_n((1,0,0), Y_{-nm}, X_{nm})$ and $\pi_n((1,0,0), Y_{-nm}, X_{nm}) - \pi_n((0,0,0), Y_{-nm}, X_{nm})$. By this observation and the definition of $\underline{\Delta}_j(X_{nm})$ and $\overline{\Delta}_j\left(X_{nm}\right)$ in equation (4), we have

$$\sum_{j\in\mathcal{J}_n} Y_{jm}\underline{\Delta}_j\left(X_{nm}\right) \leq \pi_n\left(Y_{nm}, Y_{-nm}, X_m\right) \leq \sum_{j\in\mathcal{J}_n} Y_{jm}\overline{\Delta}_j\left(X_m\right).$$

Define

$$\begin{aligned}
\tilde{\underline{\Gamma}}_{nm}\left(X_{nm}, W_{nm}, \zeta_{nm}, \theta, \sigma_\zeta\right) &= \max_{\{Y_{nm} \text{ s.t.} \sum_{j\in\mathcal{J}_n} Y_{jm}>0\}} \sum_{j\in\mathcal{J}_n} Y_{jm}\left(\underline{\Delta}_j\left(X_{nm}\right) - W_{jm}\theta - \sigma_\zeta\zeta_{jm}\right) - \theta_0, \\
\tilde{\overline{\Gamma}}_{nm}(X_{nm}, W_{nm}, \zeta_{nm}, \theta, \sigma_\zeta) &= \max_{\{Y_{nm} \text{ s.t.} \sum_{j\in\mathcal{J}_n} Y_{jm}>0\}} \sum_{j\in\mathcal{J}_n} Y_{jm}\left(\overline{\Delta}_j\left(X_{nm}\right) - W_{jm}\theta - \sigma_\zeta\zeta_{jm}\right) - \theta_0.
\end{aligned} \tag{F.1}$$

We have $\tilde{\underline{\Gamma}}_{nm}\left(X_{nm}, W_{nm}, \zeta_{nm}, \theta, \sigma_\zeta\right) \leq \underline{\Gamma}_{nm}\left(X_{nm}, W_{nm}, \zeta_{nm}, \theta, \sigma_\zeta\right)$ by the max-min inequality and $\overline{\Gamma}_{nm}\left(X_{nm}, W_{nm}, \zeta_{nm}, \theta, \sigma_\zeta\right) \leq \tilde{\overline{\Gamma}}_{nm}(X_{nm}, W_{nm}, \zeta_{nm}, \theta, \sigma_\zeta)$ by the definition of $\tilde{\overline{\Gamma}}_{nm}(X_{nm}, W_{nm}, \zeta_{nm}, \theta, \sigma_\zeta)$.

The integer programming problem in (F.1) can be solved quickly given the additive structure. Specifically,

$$\begin{aligned}
&\tilde{\underline{\Gamma}}_{nm}(X_{nm}, W_{nm}, \zeta_{nm}, \theta, \sigma_\zeta) \\
=& -\theta_0 + \begin{cases} \sum_{j\in\mathcal{J}_n}\left[\underline{\Delta}_j\left(X_{nm}\right) - W_{jm}\theta - \sigma_\zeta\zeta_{jm}\right]_+ & \text{if } \exists j \text{ s.t. } \underline{\Delta}_j\left(X_{nm}\right) - W_{jm}\theta - \sigma_\zeta\zeta_{jm} > 0, \\ \max_{j\in\mathcal{J}_n}\left\{\underline{\Delta}_j\left(X_{nm}\right) - W_{jm}\theta - \sigma_\zeta\zeta_{jm}\right\} & \text{otherwise.} \end{cases}
\end{aligned}$$

In other words, we simply need to calculate the value of each $\underline{\Delta}_j\left(X_{nm}\right) - W_{jm}\theta - \sigma_\zeta\zeta_{jm}$, sum up all the positive terms, and subtract θ_0. If $\underline{\Delta}_j\left(X_{nm}\right) - W_{jm}\theta - \sigma_\zeta\zeta_{jm} < 0$ for all $j \in \mathcal{J}_n$, we calculate the bound as the maximum of $\underline{\Delta}_j\left(X_{nm}\right) - W_{jm}\theta - \sigma_\zeta\zeta_{jm} - \theta_0$. Similarly,

$\tilde{\overline{\Gamma}}_{nm}(X_{nm}, W_{nm}, \zeta_{nm}, \theta)$ is given by

$$\begin{aligned}
&\tilde{\overline{\Gamma}}_{nm}(X_{nm}, W_{nm}, \zeta_{nm}, \theta) \\
=& -\theta_0 + \begin{cases} \sum_{j\in\mathcal{J}_n} \left[\overline{\Delta}_j\left(X_{nm}\right) - W_{jm}\theta - \sigma_\zeta\zeta_{jm}\right]_+ & \text{if } \exists j \text{ s.t. } \overline{\Delta}_j\left(X_{nm}\right) - W_{jm}\theta - \sigma_\zeta\zeta_{jm} > 0, \\ \max_{j\in\mathcal{J}_n}\left\{\overline{\Delta}_j\left(X_{nm}\right) - W_{jm}\theta - \sigma_\zeta\zeta_{jm}\right\} & \text{otherwise.} \end{cases}
\end{aligned}$$

In the end, we use the following lower and upper bounds for estimation:

$$\begin{aligned}
&\Pr\left(\tilde{\underline{\Gamma}}_{nm}\left(X_{nm}, W_{nm}, \zeta_{nm}, \theta, \sigma_\zeta\right) > 0\right) \\
&\leq \Pr\Big(\sum_{j\in\mathcal{J}_n} Y_{jm} > 0 \,|X_{nm}, W_{nm}\Big) \\
&\leq \Pr\left(\tilde{\overline{\Gamma}}_{nm}\left(X_{nm}, W_{nm}, \zeta_{nm}, \theta, \sigma_\zeta\right) > 0\right).
\end{aligned}$$

Since these bounds do not have analytic expressions, we simulate them.

We combine moments associated with firm and product entry in the estimation. For moments associated with product entry, we modify the bounds of the conditional choice probability of an individual product's outcome to take into account θ_0:

$$\begin{aligned}
&F_\zeta\left(\zeta_{jm} < (\underline{\Delta}_j\left(X_{nm}\right) - W_{jm}\theta - [\theta_0]_+)/\sigma_\zeta\right) \\
\leq& \Pr\left(Y_{jm} = 1\,|X_{nm}, W_{jm}\right) \\
\leq& F_\zeta\left(\zeta_{jm} < (\overline{\Delta}_j\left(X_{nm}\right) - W_{jm}\theta - [\theta_0]_-)/\sigma_\zeta\right).
\end{aligned}$$

The same set of non-negative g functions as those in the baseline estimation are used to construct the moments associated with individual products. For moments associated with firm entry, we use $\left(\underline{\Delta}_j(X_{nm}), \overline{\Delta}_j(X_{nm})\right)$ of the top three most profitable products of firm n to define the non-negative g functions. If a firm has only one (or two) potential products, we set the g functions corresponding with the second and third products (or the third product) to be 0.

We report the estimation results in Table F.1 and the counterfactual simulation results in Figure F.1 (merger effects on entry, product variety, and prices) and Table F.2 (welfare effects). In both tables, we include the baseline results for comparison. Figure F.1 should be compared with Figure 6. From these comparisons, we can see that while the magnitude of the estimates change, the merger effects are very similar to the baseline results.

Table F.1: Fixed Cost Estimates: Projected 95% Confidence Interval, Allowing for (Dis)Economies of Scope

	Baseline Model	(Dis)Economies of Scope
Craft (θ_1)	[163.63, 276.68]	[11.06, 394.75]
In State× Craft (θ_2)	[-77.54, 33.50]	[-164.29, 260.59]
Market-size specific fixed cost (θ_3)		
Small market	[631.37, 759.29]	[985.41, 1453.54]
Medium market	[822.40, 934.80]	[454.44, 990.60]
Large market	[1902.60, 1998.82]	[3072.07, 3536.96]
Market-size specific std. dev. (σ_ζ)		
Small market	[212.62, 321.91]	[85.80, 454.08]
Medium market	[309.36, 414.19]	[253.50, 614.73]
Large market	[878.99, 995.72]	[962.06, 1452.46]
Market-size specific firm entry cost (θ_0)		
Small market		[-863.01, -436.36]
Medium market		[241.61, 640.43]
Large market		[-1415.72, -951.47]

Note: Estimates in 2016 US dollars.

Table F.2: Welfare Effects, Allowing for (Dis)Economies of Scope

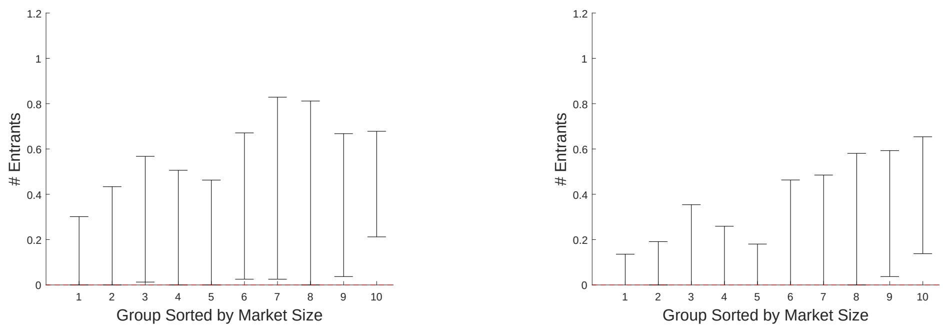
		No Merger Efficiency	With Merger Efficiency
Baseline			
(1)	consumer surplus ($1000)	[-842.62, -263.47]	[-591.56, -103.63]
(2)	craft beer profits ($1000)	[35.56, 174.94]	[32.29, 178.38]
(3)	total surplus ($1000)	[-698.81, -227.33]	[-436.78, -64.08]
Allowing for (Dis)Economies of Scope			
(1)	consumer surplus ($1000)	[-867.92, -244.00]	[-717.41, -62.10]
(2)	craft beer profits ($1000)	[23.90, 141.64]	[24.45, 129.94]
(3)	total surplus ($1000)	[-734.31, -220.09]	[-634.31, -25.83]

Note: this table reports the aggregate welfare effects of the merger across markets. For each measure, we report the range across the vectors of parameters sampled from their 95% confidence set. The left panel shows the results without considering any merger efficiency, while the right panel reports the results that incorporate reductions in fixed costs when a craft brewery is acquired by a macro brewery.

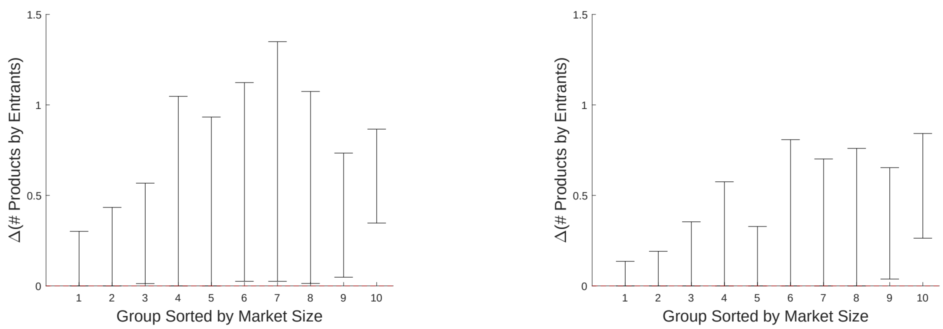
Figure F.1: Merger Effects on Entry, Product Variety, and Prices, Allowing for (Dis)Economies of Scope

No Merger Efficiency | With Merger Efficiency

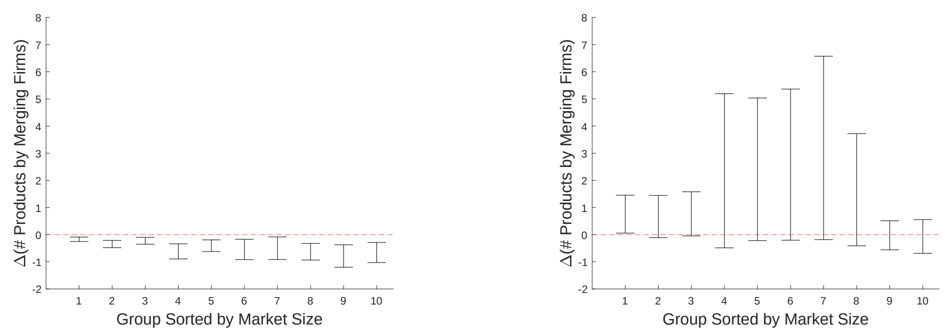
(A) Number of Entrants



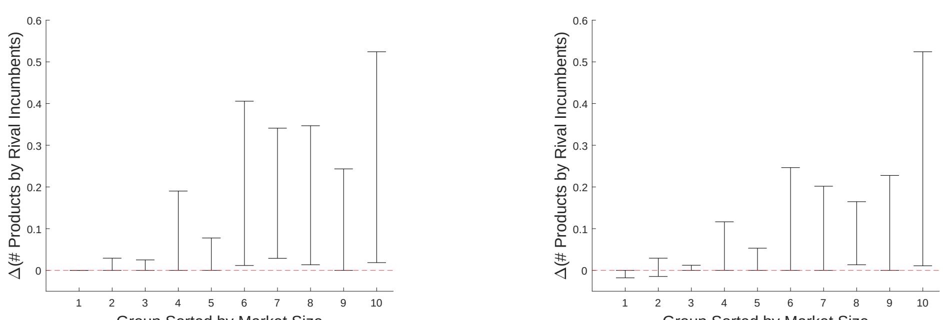
(B) Number of Products Added by Entrants



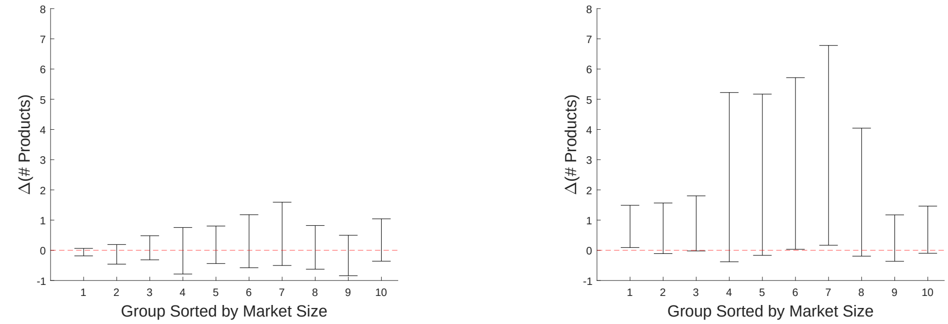
(C) Change in the Number of Products by Merging Firms



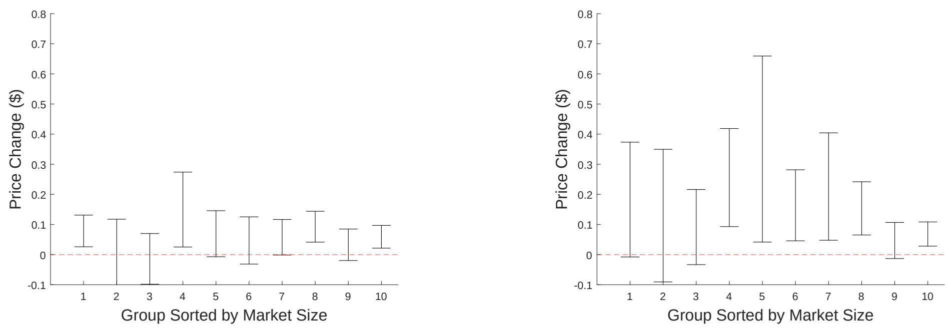
(D) Change in the Number of Products by Non-merging Incumbent Firms



(E) Change in the Number of Products



(F) Change in Craft Prices



G Robustness Analysis: Correlated Fixed Cost Shocks

In the paper, we assume that unobservable fixed cost shocks are i.i.d. In this section, we extend the model to allow for correlated shocks. We start with explaining how an additional set of bounds can be constructed and used to identify the correlation using the illustrative example in Section 2.1. We then extend our empirical model in Section 4 and show robustness of our estimation results to allowing for a market-wide shock common to all products.

Extension to the Illustrative Model and Additional Bounds

To estimate the correlation in unobserved cost shocks, we bound the joint entry probabilities of multiple firms or products. We first explain the extension using the illustrative example in Section 2.1. We consider bounding the probability of $\Pr(Y_{1m}=1, Y_{2m}=1)$. The level-1 rationality assumption implies the following:

$$
\begin{aligned}
&\Pr\left(Y_{nm}=1 \text{ is a dominant strategy for both } n=1 \text{ and } n=2\right)\\
\leq &\Pr\left(Y_{1m}=1, Y_{2m}=1\right)\\
\leq &\Pr\left(Y_{nm}=1 \text{ is not a dominant strategy for either } n=1 \text{ or } n=2\right).
\end{aligned}
$$

To save notation, we define $\overline{\pi}_{nm} = \max\left(\pi_{nm}(0), \pi_{nm}(1)\right)$ and $\underline{\pi}_{nm} = \min\left(\pi_{nm}(0), \pi_{nm}(1)\right)$. We also use $F_{\zeta_1\zeta_2}$ to denote the joint distribution of (ζ_{1m}, ζ_{2m}). The bounds above can be expressed as

$$\begin{aligned} & F_{\zeta_1\zeta_2}\left(\underline{\pi}_{1m} - C_{1m}, \underline{\pi}_{2m} - C_{2m}\right) \\ \leq & \Pr\left(Y_{1m} = 1, Y_{2m} = 1\right) \\ \leq & F_{\zeta_1\zeta_2}\left(\overline{\pi}_{1m} - C_{1m}, \overline{\pi}_{2m} - C_{2m}\right), \end{aligned} \tag{G.1}$$

which can be rewritten as

$$\begin{aligned} & \Pr\left(\zeta_{1m} < \underline{\pi}_{1m} - C_{1m} \left| \zeta_{2m} < \underline{\pi}_{2m} - C_{2m}\right.\right) \cdot \Pr\left(\zeta_{2m} < \underline{\pi}_{2m} - C_{2m}\right) \\ \leq & \Pr\left(Y_{1m} = 1, Y_{2m} = 1\right) \\ \leq & \Pr\left(\zeta_{1m} < \overline{\pi}_{1m} - C_{1m} \left| \zeta_{2m} < \overline{\pi}_{2m} - C_{2m}\right.\right) \cdot \Pr\left(\zeta_{2m} < \overline{\pi}_{2m} - C_{2m}\right). \end{aligned}$$

As the correlation between ζ_{1m} and ζ_{2m} increases, both $\Pr(\zeta_{1m} < \underline{\pi}_{1m} - C_{1m} \left| \zeta_{2m} < \underline{\pi}_{2m} - C_{2m}\right.)$ and $\Pr\left(\zeta_{1m} < \overline{\pi}_{1m} - C_{1m} \left| \zeta_{2m} < \overline{\pi}_{2m} - C_{2m}\right.\right)$ increase, making the lower bound more likely to be violated. Conversely, as the correlation decreases, both conditional probabilities decrease, making the upper bound more likely to be violated. Therefore, these bounds are informative about the correlation.

Extension to the Empirical Model

We extend the fixed cost specification to allow for a market-level unobserved cost shock ζ_m:

$$W_{jm}\theta + \sigma_\zeta \zeta_{jm} + \sigma \zeta_m,$$

and estimate the standard deviation σ. We assume ζ_m is i.i.d. across markets and has a standard normal distribution.

In this model, for two potential products (j, j'), the analogy of inequality (G.1) is:

$$\begin{aligned} & \Phi\left(\underline{\Delta}_j\left(X_{nm}\right) - c\left(W_{jm}, \theta\right), \underline{\Delta}_{j'}\left(X_{nm}\right) - c\left(W_{j'm}, \theta\right); \Sigma\right) \\ \leq & \Pr\left(Y_{jm} = 1, Y_{j'm} = 1 \left| X_{nm}, W_{jm}, W_{j'm}\right.\right) \\ \leq & \Phi\left(\overline{\Delta}_j\left(X_{nm}\right) - c\left(W_{jm}, \theta\right), \overline{\Delta}_{j'}\left(X_{nm}\right) - c\left(W_{j'm}, \theta\right); \Sigma\right), \end{aligned}$$

where Φ is the bivariate normal distribution with zero means and the covariance matrix

$$\Sigma = \begin{pmatrix} \sigma_\zeta^2 + \sigma^2 & \sigma^2 \\ \sigma^2 & \sigma_\zeta^2 + \sigma^2 \end{pmatrix}.$$

The resulting new moment functions are

$$\begin{aligned} & L\left(Y_{jm}, Y_{j'm}, X_{nm}, W_{jm}, W_{j'm}, \theta, \Sigma\right) \\ & = \Phi\left(\underline{\mathit{\Delta}}_j\left(X_{nm}\right) - c\left(W_{jm}, \theta\right), \underline{\mathit{\Delta}}_{j'}\left(X_{nm}\right) - c\left(W_{j'm}, \theta\right); \Sigma\right) \\ & - \mathbb{1}\left(Y_{jm} = 1, Y_{j'm} = 1\right) \end{aligned}$$

and

$$\begin{aligned} & H\left(Y_{jm}, Y_{j'm}, X_{nm}, W_{jm}, W_{j'm}, \theta, \Sigma\right) \\ & = \mathbb{1}\left(Y_{jm} = 1, Y_{j'm} = 1\right) \\ & - \Phi\left(\overline{\mathit{\Delta}}_j\left(X_{nm}\right) - c\left(W_{jm}, \theta\right), \overline{\mathit{\Delta}}_{j'}\left(X_{nm}\right) - c\left(W_{j'm}, \theta\right); \Sigma\right). \end{aligned}$$

We combine the moments based on a single product's entry probability in the main text of the paper with the following additional moments in estimation:

$$\begin{aligned} & E\left[\frac{1}{\frac{1}{2}J\left(J-1\right)}\sum_{j=2}^{J}\sum_{j'=1}^{j-1} L\left(Y_{jm}, Y_{j'm}, X_{nm}, W_{jm}, W_{j'm}, \theta, \Sigma\right) \cdot g^{(k)}\left(X_{nm}, W_{jm}\right)\right] \leq 0, \\ & E\left[\frac{1}{\frac{1}{2}J\left(J-1\right)}\sum_{j=2}^{J}\sum_{j'=1}^{j-1} L\left(Y_{jm}, Y_{j'm}, X_{nm}, W_{jm}, W_{j'm}, \Sigma, \theta\right) \cdot g^{(k)}\left(X_{nm}, W_{j'm}\right)\right] \leq 0, \\ & E\left[\frac{1}{\frac{1}{2}J\left(J-1\right)}\sum_{j=2}^{J}\sum_{j'=1}^{j-1} H\left(Y_{jm}, Y_{j'm}, X_{nm}, W_{jm}, W_{j'm}, \Sigma, \theta\right) \cdot g^{(k)}\left(X_{nm}, W_{jm}\right)\right] \leq 0, \\ & E\left[\frac{1}{\frac{1}{2}J\left(J-1\right)}\sum_{j=2}^{J}\sum_{j'=1}^{j-1} H\left(Y_{jm}, Y_{j'm}, X_{nm}, W_{jm}, W_{j'm}, \theta, \Sigma\right) \cdot g^{(k)}\left(X_{nm}, W_{j'm}\right)\right] \leq 0, \end{aligned}$$

where $g^{(k)}$ is defined in Supplemental Appendix D.

Robustness Results

Table G.1 reports our estimation results. We find that a fairly modest standard deviation of the market-level shock ζ_m compared to the standard deviation of the product/market-level shock ζ_{jm}. The estimates of parameters common to the baseline and extended specifications are robust.

Table G.1: Fixed Cost Estimates: Projected 95% Confidence Interval, Allowing for a Market-Level Shock

	Baseline Model	With a Market-level Shock
Craft (θ_1)	[163.63, 276.68]	[138.91, 315.26]
In State× Craft (θ_2)	[-77.54, 33.50]	[-127.44, 18.88]
Market-size specific fixed cost (θ_3)		
Small market	[631.37, 759.29]	[644.92, 887.76]
Medium market	[822.40, 934.80]	[746.44, 927.74]
Large market	[1902.60, 1998.82]	[1699.00, 1900.87]
Market-size specific std. dev. (σ_ζ)		
Small market	[212.62, 321.91]	[245.41, 360.08]
Medium market	[309.36, 414.19]	[316.87, 413.17]
Large market	[878.99, 995.72]	[501.43, 700.02]
Market-level unobserved cost std. dev. (σ)		[0.00, 160.76]

Note: Estimates in 2016 US dollars.