Merger, Product Variety and Firm Entry: the Retail Craft Beer Market in California*

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Abstract

We study the effects of merger on firm entry, product variety and prices in the retail craft beer market in California. We develop a new method to estimate multiple-discrete choice models in order to recover fixed costs. The method is based on bounds of conditional choice probabilities and does not require solving a game. Using the estimated model, we simulate a counterfactual merger where a large brewery acquires multiple craft breweries. In most markets, we find that new firms enter, non-merging incumbents add products, and merging firms drop products. However, the net effects of product variety from new firm entry and incumbent product portfolio adjustment differ considerably across markets. Larger markets are more likely to see an increase in product variety, which moderates the loss of consumer surplus from the merger's price effects. In a majority of smaller markets, product variety decreases, exacerbating the welfare loss from the price effects.

1 Introduction

In antitrust litigation, merging parties could defend a merger proposal by using the potential entry argument: if a merger leads to increases in prices, the resulting greater profit opportunity will attract entry, which then compensates for the lost competition and thus curbs the price increase, mitigating the negative effect of the merger. One assumption behind this argument is that the incumbent firms do not change their product offerings. Does a merger cause the incumbents to add or drop products? Does entry occur? What is the overall impact of product change and firm entry on welfare? Does the changes of product variety offset the negative price effects? How do all

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these effects vary across markets? In this paper, we address these questions and study the effects of merger on prices, product portfolios and firm entry in the context of the retail craft beer market in California.

The craft beer industry provides an ideal empirical context to study the effects of merger on the entry and product variety of multi-product firms. The craft industry is a growing segment of the beer industry. Between 2006 and 2016, while major breweries such as ABI and MillerCoors saw the sales of their main (non-craft) products plateau, the craft beer market experienced substantial growth in variety and sales (Hart and Alston (2019)). Craft breweries have thus become popular targets of acquisitions, attracting the concerns of the antitrust regulators (Codog (2018)). In addition, there are rich demographic variations across geographical markets that help to identify consumer tastes and incentives of entry and product choice. We focus on the state of California, which has the largest number of craft breweries and the highest craft beer production among the US states, with 462 craft breweries (12% of all US craft breweries) and 43 million barrels of production (18% of all US craft beer production) in 2015, according to the Brewers Association, a trade group in the beer industry.

To address our research questions, we set up a model to describe demand and firm decisions in the retail beer market in California. The demand side is a discrete choice model where we allow for both observed and unobserved heterogeneity in consumer tastes. The supply side is a static two-stage model. In the first stage, firms are endowed with a set of each potential product, and choose the set of products to sell in a market. A firm can choose an empty set, indicating no entry. In the second stage, firms observe shocks to demand and marginal costs and choose prices simultaneously. The structure of the game is similar to the prior empirical work on product variety (e.g., Eizenberg (2014); Wollmann (2018); Fan and Yang (2020)).

Our main data sources are Nielsen Retail Scanner Data and Nielsen Consumer Panel from 2009 to 2016. We supplement the data with information on whether a beer is considered craft using data from the Brewers Association. We further augment the data by hand-collecting the owner and brewery identities and the location of the brewery for each beer.

The key primitives in the second stage of our model are consumer preferences and marginal costs. We estimate beer demand with data on market shares and panel data of individual choices. The first-order conditions for the optimal prices allow us to estimate marginal costs.

The key primitives in the first stage of the model are the fixed costs of product entry into markets. Both the merger outcomes and welfare predictions depend critically on the estimates of the fixed costs. We estimate the distribution of fixed costs with a new method that takes into account selection on fixed cost unobservables. Our method relies on a construction of two-sided bounds for the probability that a product is in a market. The construction is based on the following intuition: for a binary action a, the equilibrium choice 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. In the paper, we explain the assumption on firm equilibrium behavior, explain these bounds, and provide details on estimation and inference.

Using the estimated model, we simulate the effects of a counterfactual merger where the largest macro brewery acquires three large craft breweries in 2016. We find that the merger causes new firm entry and these new entrants add to product variety in most markets. At the same time, merging firms tend to drop products, while the non-merging incumbents tend to add products. The net changes of variety (from new entry and incumbents' product adjustment) and the associated welfare impacts are quite heterogeneous across markets. Larger markets are more likely to see an increase in the number of products and a positive welfare effect attributed to variety changes. In this case, we find that the positive product variety effects partially offsets the negative price effects. In smaller markets, the net change in product variety tends to be negative, which exacerbates the negative price effects. Across markets, new entry occurs, but its positive welfare effect is small relative to the total consumer welfare loss. We show how these welfare changes are related to product substitutability, fixed costs and market sizes. In this paper, we study a setting where firms decide on whether to distribute an existing product to a market, and we do not consider (potentially dynamic) innovation or product development costs, which may be higher than the static fixed costs of entry. We find that even in our static setting that favors product entry, the product variety effect of a merger is either negative or not big enough to overcome the consumer surplus loss.

Contributions and Literature Review Our contributions are two-fold. First, we contribute to the literature of merger and product variety. In this paper, we consider the entry of firms and products in the context of multi-product firms. Entry defense has long been recognized in policy guidelines and investigated in both theoretical (for example, Spector (2003); Anderson et al. (2020); Caradonna et al. (2020)) and simulation or empirical studies (for example, Werden and Froeb (1998); Cabral (2003); Gandhi et al. (2008); Ciliberto et al. (2020)). Different from these papers, which focus on entry of single-product firms, we consider multi-product firms. Therefore, it is possible in our model for a merger to decrease product variety even when the merger causes entry, because the incumbents can reduce product offerings. The US Horizontal Merger Guidelines have started to recognize the roles of product variety in a merger.[1] Recent academic work has sought to empirically quantify how merger affects product variety and the associated welfare impact (Fan (2013); Wollmann (2018); Li et al. (2019); Fan and Yang (2020); Garrido (2020)) while disallowing firm entry.[2] For the retail craft beer market in California, we show significant heterogeneity in entry, incumbents' product adjusmtnet and the net changes of variety across markets. We show that the size of the market, the market power of the merging firms and the fixed costs of the merging firms and their rivals are important determinants of the merger outcomes.

[1] The 2010 Guidelines state, "(t)he Agencies also consider whether a merger is likely to give the merged firm an incentive to cease offering one of the relevant products sold by the merging parties. Reductions in variety following a merger may or may not be anti–competitive. Mergers can lead to the efficient consolidation of products when variety offers little in value to customers. In other cases, a merger may increase variety by encouraging the merged firm to reposition its products to be more differentiated from one another". In comparison, the 1997 US Merger Guidelines did not explicitly mention the roles of product variety.

[2] In the radio industry, a number of papers (e.g., Berry and Waldfogel (2001); Sweeting (2010); Jeziorski (2015)) have studied merger, entry and variety but do not quantify the impact on consumer welfare because radio stations do not set prices to listeners.

Our second contribution is a new method for estimating multiple-discrete choice games. The simulations to quantify the extent of entry and product variety changes critically depend on the estimates of fixed costs. We allow fixed costs to depend on observable covariates such as distance as well as an unobservable fixed cost shock and estimate fixed cost parameters by constructing bounds for the conditional choice probability (CCP) that a product is in a market conditional on the primitives of the market. The lower bound is the probability that the fixed cost shock is low such that including the product in a firm's product portfolio is a dominant strategy. The upper bound is one minus the probability that the fixed cost shock is high such that including the product is a dominated strategy. These bounds hold when there are multiple equilibria, under any equilibrium selection rules, and even when the selection rules vary across markets. They do not rely on the existence of a pure strategy equilibrium either. More importantly, computing these bounds does not require solving for an equilibrium of product choices and only involves evaluating one-dimensional cumulative distribution functions.

Our method is similar to Ciliberto and Tamer (2009) in two dimensions: both approaches specify the distribution of the fixed cost shocks and both models are incomplete in the sense of not predicting a unique outcome. The key difference between the two approaches is the construction of the bounds. Ciliberto and Tamer (2009) construct bounds for the probability of an outcome being an equilibrium. The lower and upper bounds consist of the probability that an outcome is the unique equilibrium and the probability that the outcome is one of the potentially multiple pure-strategy equilibria. Therefore, to compute these bounds in estimation, one has to simulate multiple fixed cost draws, and for each simulation draw, solve for all equilibria. This can be computationally costly if not prohibitive for a multi-product firm in a game with many firms, which is the case in our empirical setting. We construct bounds for the CCP of a single action regarding a product in a market. These bounds are probabilities of whether a one-dimensional shock is above or below certain cutoffs. Computing these cutoffs does not require solving the game. Our approach therefore is especially applicable to estimating games with many players and/or when the decision of a player can be represented as a (potentially very long) vector of binary decisions.[3]

Another approach in the literature of 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 (e.g., Ho (2009); Eizenberg (2014); Pakes et al. (2015); Wollmann (2018)). Such an approach typically relies on a mean zero or conditional mean zero assumption, and sets the error term in the fixed cost function to be zero in counterfactual simulations. We find that the variance of the fixed-cost shocks is substantial in our empirical application.

Our paper is also related to two recent papers on entry (Ciliberto et al. (2020)) and product repositioning (Li et al. (2019)) in the airline industry. There are three modeling differences. First, in our model, the decision of a firm is a vector of binary decisions regarding each of the firm's potential products. In contrast, firms make a single binary decision on either entry (Ciliberto

[3]By using empirical estimates of CCP in moment inequalities, our method is related to the CCP approach in the estimation of dynamic models (e.g., Bajari et al. (2007)).

et al. (2020)) or whether to provide non-stop service (Li et al. (2019)). Therefore, we discuss product variety together with firm entry,[4] and we use a new method to address the estimation challenges that arise from allowing for a larger action space. In our model, even when a merger causes entry, the overall product variety can decrease when the (multi-product) incumbents reduce product offerings. Second, Ciliberto et al. (2020) and Li et al. (2019) assume that firms observe demand and marginal cost shocks as well as fixed cost shocks when the firms make decisions on entry, thus accounting for selection on unobserved demand and marginal costs, in addition to the selection on unobserved fixed cost shocks. We allow for the latter selection only and address the selection on demand and marginal costs by including a large number of fixed effects in our demand and marginal cost functions. The remaining unobservables are transient shocks, and we find it reasonable to assume firms do not observe them when making product choices. We also show that these transient shocks are small. Third, related to the second point, Ciliberto et al. (2020) and Li et al. (2019) allow for correlations among unobserved demand, marginal cost and fixed cost shocks. We include common observable covariates in demand, marginal cost and fixed cost shocks to allow for correlation through observables.

In a recent paper, Wang (2020) proposes a hybrid approach that combines the framework in Ciliberto et al. (2020) with probability bounds based on the concept of dominant strategies. The computational burden of such an approach is between our methods and Ciliberto et al. (2020).

Overall, we consider our approach complementary to existing papers on estimating discrete games. Our approach is suitable for a setting where solving for equilibria is costly and the unobserved shock to the fixed-cost of entry is potentially important to address the research questions of interest.[5]

The rest of the paper is organized as follows. We first use an illustrative model to explain our bounds in Section 2. Section 3 discusses the craft beer market in California and the data. Section 4 presents the model. Section 5 explains the estimation strategy and in particular, provide details on implementing our new estimation method. The estimation results are presented in Section 6. Section 7 describes the counterfactual designs and results. Finally, we conclude in Section 8.

2 An Illustrative Model

In this section, we use a two-firm entry model to illustrate how we construct our bounds used for estimation. Later, we extend the model to N firms and multiple binary decisions and explain

[4] Seim (2006) and Draganska et al. (2009) also study entry with endogenous product choice but in an incomplete information framework.

[5] There are three other alternative estimation approaches. First, one can reduce the number of equilibria with additional assumptions. When the action space of players is small, one could then estimate the model with maximum likelihood (Reiss and Spiller (1989); Garrido (2020)) or simulated method of moments (Berry (1992); Li et al. (2019)). Alternatively, Illanes (2017) estimates a dynamic discrete choice problem using a semi-parametric latent variable integration method (Schennach (2014)) to deal with selection in unobservables. Like us, this approach also avoids solving a game or an optimization problem, but can result in relatively wide (and sometimes unbounded) confidence sets of parameters. Finally, Fan and Yang (2020) directly make assumptions about the distribution of the unobserved fixed cost shock conditional on the observed equilibrium for their merger simulations. In comparison, the approach in this paper estimates this distribution.

identification and estimation details.

In this illustrative model, firms 1 and 2 decide whether to enter market m according to

$$\begin{aligned} Y_{1m} &= 1\left[\pi_{1m}\left(Y_{2m}\right) - C\left(W_{1m}, \theta\right) - \zeta_{1m} \geq 0\right], \\ Y_{2m} &= 1\left[\pi_{2m}\left(Y_{1m}\right) - C\left(W_{2m}, \theta\right) - \zeta_{2m} \geq 0\right], \end{aligned} \tag{1}$$

where $Y_{jm} = 1$ indicates entry. In (1), $\pi_{jm}\left(Y_{-jm}\right)$, $j \in \{1, 2\}$ is a variable profit function that is known (or has been estimated), $C\left(W_{jm}, \theta\right)$, $j \in \{1, 2\}$ is the fixed cost of entry, where W_{jm} is a vector of covariates and θ is a vector of parameters to be estimated, and finally, ζ_{jm} is a fixed cost shock known to the firms but unobserved by the researchers. The shock ζ_{jm} is assumed to follow the distribution $F_{\zeta}\left(\zeta; \sigma_{\zeta}\right)$, where σ_{ζ} represents distributional parameters to be estimated.

This model poses well–known estimation challenges due to the presence of multiple equilibria and unspecified equilibrium selection rule. Estimation needs to deal with the following selection problem: conditional on observed entry decisions, the unobservable fixed cost shocks for the entered products and not-entered products have different distributions. We discussed some of the existing methods in the literature review part of the Introduction. Our new approach is to construct bounds for the conditional choice probability (CCP), $\Pr\left(Y_{jm} = 1 \left| W_{jm}, W_{-jm}\right.\right)$. Specifically, we consider the following behavioral assumption that is weaker than Nash equilibrium:

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

The assumption implies the following bounds for the CCP $\Pr\left(Y_{jm} = 1 \left| W_{jm}, W_{-jm}\right.\right)$:

$$\begin{aligned} &\Pr\left(Y_{jm} = 1 \text{ is a dominant strategy } \left| W_{jm}, W_{-jm}\right.\right) \\ \leq &\Pr\left(Y_{jm} = 1 \left| W_{jm}, W_{-jm}\right.\right) \\ \leq &\Pr\left(Y_{jm} = 1 \text{ is not a dominated strategy } \left| W_{jm}, W_{-jm}\right.\right). \end{aligned} \tag{2}$$

The model implications for the lower bound and the upper bounds in (2) are, respectively,

$$\Pr\left(\zeta_{jm} < \min\left\{\pi_{1m}\left(0\right), \pi_{1m}\left(1\right)\right\} - C\left(W_{1m}, \theta\right) \left| W_{jm}, W_{-jm}\right.\right)$$

and

$$1 - \Pr\left(\zeta_{jm} > \max\left\{\pi_{1m}\left(0\right), \pi_{1m}\left(1\right)\right\} - C\left(W_{jm}, \theta\right) \left| W_{jm}, W_{-jm}\right.\right).$$

Therefore,

$$\begin{aligned} &F\left(\min\left\{\pi_{1m}\left(0\right), \pi_{1m}\left(1\right)\right\} - C\left(W_{jm}, \theta\right); \sigma_{\zeta}\right) \\ \leq &\Pr\left(Y_{jm} = 1 \left| W_{jm}, W_{-jm}\right.\right) \\ \leq &F\left(\max\left\{\pi_{1m}\left(0\right), \pi_{1m}\left(1\right)\right\} - C\left(W_{jm}, \theta\right); \sigma_{\zeta}\right). \end{aligned} \tag{3}$$

We explain estimation and inference based on these bounds in details in Section 5. Here, we highlight the advantages of using our constructed bounds for estimation. First, these bounds contain useful information on the fixed cost function. Consider the extreme case where $\pi_{jm}(1) = \pi_{jm}(0)$. The inequalities collapse into an equality, and estimation becomes GMM estimation of binary choice models (McFadden (1989)). Therefore, intuitively, the usefulness of the inequalities for estimating fixed cost parameters depends on the gap between $\pi_{jm}(1)$ and $\pi_{jm}(0)$, which we explore in the later estimation section and through Monte Carlo exercises. Second, these bounds are one-dimensional CDFs and easy to compute. Computing them does not suffer from a dimensionality problem in a game with more firms. Third, the bounds do not rely on equilibrium selection assumptions. Specifically, these bounds hold when there are multiple equilibria, the equilibrium selection mechanism differs across markets, or there is no pure strategy equilibrium.

3 Industry and Data

Our empirical analysis focuses on the retail craft beer market in the state of California. 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. Moreover, California has accommodating distribution laws. California places no cap on the volume a brewery can distribute its products without a third-party distributor, essentially empowering breweries to become distributors if the costs of distributing through third parties are too high (Anhalt (2016)). California beer statues do not require breweries to satisfy a burdensome "good cause" clause to terminate a contract with a distributor. Taken together, we find it reasonable to assume that the distribution market is sufficiently competitive,[6] and we do not consider the strategic behaviors of distributors in our model later.[7] Furthermore, in addition to federal statues that prohibit "tied-houses", vertical relationships between manufacturers and retailers that exclude small alcoholic beverage makers such as craft breweries from retailers, California additionally passed its own "tied-house" laws and unfair competition laws to prevent exclusion (Croxall (2019)). These institutional features motivate our modeling assumption that beer firms make the entry and product variety decisions based on the retail profitability of their products. The simplifications keep our model tractable and allow us to focus on the entry and product variety decision of breweries.

Our analysis is based on the product, sales and price information of beers sold in major retailer chains in the Nielsen data. We use both the aggregate data in the Nielsen Retail Scanner Data and the micro-level panel data in the Nielsen Consumer Panel between 2009 and 2016. We supplement the data with information on whether a beer is considered craft based on the designation by the Brewers Association. We further add hand-collected data on the identities of the owner and

[6] In 2020, California has a population of 39 million and 3178 licensed distributors. In comparison, Michigan, a state with beer restrictions similar to the majority of US states, has a population of 10 million and 160 distributors.

[7] We note that the loosening of craft beer distribution laws has become a recent national trends. For example, in 2019, North Carolina enacted the Craft Beer Distribution and Modernization Act (HB 363) to increase the quota that a craft brewery can self distribute without a distributor, and Maryland both increased the quota and reduced the burden of a "good cause" termination with Brewery Modernization Act and Beer Franchise Law (HB1010, HB1080). Similar changes have occurred or are proposed in Illinois, Massachusetts, Tennessee, Texas and other states.

brewery and the location of the brewery of each product in our data. Finally, we merge the data with county demographics from the Census. We define a firm to be a corporate owner (e.g., Boston Beer Company) and a product to be a brand (e.g., Samuel Adams Boston Lager). A firm can own multiple breweries and products. We aggregate the Nielsen data from its original UPC/week level to the product/month level by homogenizing the size of a product (so that a unit is a 12-ounce-12-pack equivalent) and adding quantities across weeks within a month and using the quantity-weighted average price across weeks within a month as the product's price in that month.

We define a market as a retailer-county pair. Our data suggest cross-retailer shopping appears rare: more than 80% of the households purchased all of their beers from one retailer-county combination in 2016. Similarly, Huang et al. (2020) and Illanes and Moshary (2020) find little evidence of retailer competition in the spirit category.

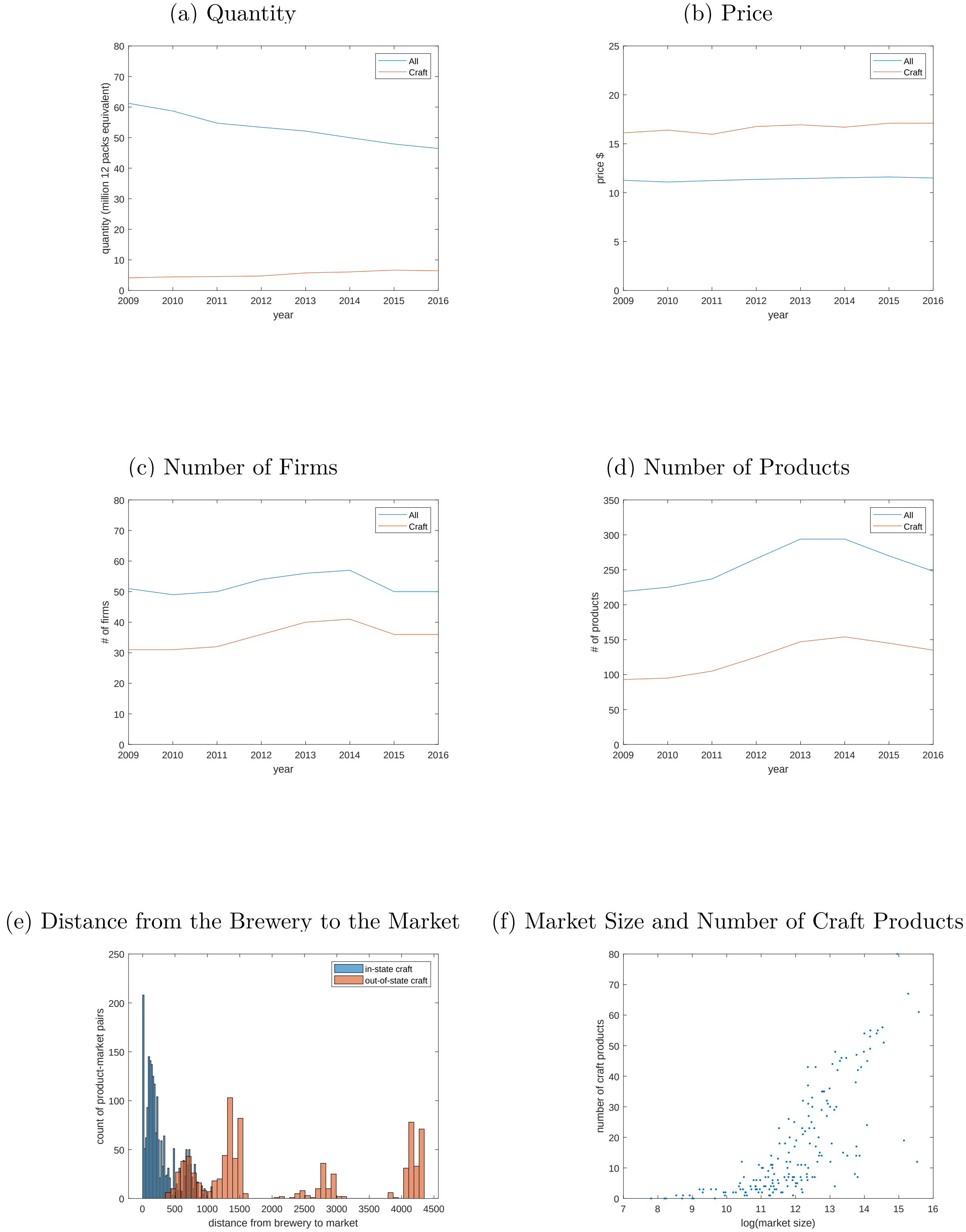
We consider a product was "in" a market in a calendar year if the product sold more than 20 units in a month for more than 6 months in the market in the year. Moreover, for craft products, we keep those by the top 60 craft breweries (by national volume in 2015) in the Brewers Association production data. We thus focus on breweries established in the 1990s or earlier. Many of these craft breweries had sold beers on their own premise and through other avenues before entering the retailers in the Nielsen data. We do not consider the potentially dynamic problem of new brewery or brand creation. In the end, our sample covers 83% of California craft beer quantity in the Nielsen Scanner Data. Although it is not possible to directly compare the importance of the retail craft beer market with the "on-premise" market (such as taprooms, bars and restaurants) using our data, which cover just the retail segment, the Brewers Association suggested that on-premise channels account for 35% of the craft volume (Watson (2016)).[8]

The number of markets, firms and products vary across the years. In 2016, there are 178 markets, 51 firms, 37 craft firms, 255 products and 111,219 product-market-month observations. We provide summary statistics year by year in Figure 1. To make the time-series comparable, we condition on the 109 markets present in every year from 2009 to 2016. All dollar values are in 2016 dollars. The total annual beer sales from these markets decreased from 61 to 46 million units (12-ounce-12-pack), while the craft sales increased from 4.1 million in 2009 to 6.4 million units in 2016 (Figure 1 (a)). The average price is stable around 11 dollars per unit. The average price of craft products increased from 16 to 17 dollars (Figure 1 (b)). There are an average of 52 firms in total and 35 craft firms (Figure 1 (c)). Both the numbers of firms and products first increased and then decreased over time, driven by changes in the numbers of craft firms and products. In the 109 markets present through all years in our data, there were 31 craft firms and 93 craft products in 2009, compared with 36 craft firms and 135 craft products in 2016 (Figure 1 (c) and Figure 1 (d)). The general trend is similar if we include all the markets in each year.

We highlight two data features that motivate our modeling choices and identification strategies. First, in Figure 1 (e), we plot the histogram of the distance from a product's brewery to a market

[8]Probably due to similar data limitations, prior work on the beer industry (Ashenfelter et al. (2015); Asker (2016); Miller and Weinberg (2017); Miller et al. (2019)) have also focused on the retail segment.

Figure 1: Summary Statistics



in 2016. The y–axis shows the count of the unique product-market pairs in the data. The majority of the in-state craft breweries distribute close to their breweries. The distance potentially plays important roles in the demand, marginal cost and fixed cost of a craft beer: a popular local beer may struggle to gain traction in markets further away, because it lacks the name recognition of the well-known national brands (Tamayo (2009)); the transportation cost factors into the marginal cost of a beer (Ashenfelter et al. (2015)); it may be hard to secure a reliable long-distance distributor. We explicitly account for these product-market effects in our demand, marginal cost and fixed cost estimation. This effect of distance on entry is less obvious for the out-of-state craft beers produced by larger breweries.

In Figure 1 (f), we show that there is a strong positive correlation between the size of a market and the number of craft products in the market. We define the market size as the average monthly alcohol sales in a market (in the unit of a 12-once-12-pack equivalent) times 8, which is the median number of household trips to a retail store in the panel data.[9] While Figure 1 (f) only plots market size and the number of products for our 178 markets in 2016, the plots for other years are similar. The local population and retailer chain variations drive the variations in market sizes, which could affect profits and thus product choice and entry. We leverage this variation (in addition to the variations of other covariates such as distances from a brewery to different markets) to identify the fixed costs of entry.

4 Model

4.1 Demand

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

$$\begin{aligned} u_{ijmt} =& (\sigma_0 \nu_i + \kappa_0 y_i) + (\alpha + \kappa_\alpha y_i)\, p_{jmt} \\ &+ \sigma^{\text{lager}} \nu_i^{\text{lager}} x_j^{\text{lager}} + \sigma^{\text{light}} \nu_i^{\text{light}} x_j^{\text{light}} + \sigma^{\text{import}} \nu_i^{\text{import}} x_j^{\text{import}} \\ &+ (\sigma^{\text{craft}} \nu_i^{\text{craft}} + \kappa^{\text{craft}} y_i) x_j^{\text{craft}} \\ &+ \xi_t + \xi_{jm} + \xi_{jmt} + \varepsilon_{ijmt}, \end{aligned} \tag{4}$$

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

where y_i is the household income and $\nu_i^{(\cdot)}$ is the household-specific unobserved taste shock to each product attribute, which follows a standard normal distribution and is independent across households. Therefore, the $\sigma^{(\cdot)}$ parameters capture the dispersion in unobserved household tastes, and the $\kappa^{(\cdot)}$ parameters measure the effect of household income on tastes. We also include month fixed effects (ξ_t) and product-market fixed effects (ξ_{jm}) to capture unobserved factors that vary across months and product-market pairs. The error term ξ_{jmt} captures the month-to-month variations of demand shocks specific to a product, market and month combination. We do not include mean coefficients for $\boldsymbol{x}_j$ because they are absorbed in fixed effects ξ_{jm}. Finally, the last term in (4), ε_{ijmt},is the household idiosyncratic taste, which is assumed to be i.i.d. and follows type-1 extreme value distribution.

This specification gives us the market share $s_{jmt}(p_{jmt}, p_{-jmt})$, corresponding with the familiar mixed Logit choice probability formula (Berry et al. (1995); Nevo (2001)), of product 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 gives us the demand for product j, $D_{jmt}(p_{jmt}, p_{-jmt})$.

4.2 Supply

The supply side is a two-stage static model. In each market, firms simultaneously choose which beers, if any, to sell. This product choice is made at the beginning of each year τ and is fixed through the year. We use $\mathcal{J}_{nm\tau}$ to denote firm n's products in market m in year τ. Then, in each month t, after observing that month's demand and marginal cost shocks, firms simultaneously choose retail prices.[10] We start from the second stage.

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

$$\max_{p_{jmt}, j \in \mathcal{J}_{nm\tau}} \sum_{j \in \mathcal{J}_{nm\tau}} \left(p_{jmt} - mc_{jmt}\right) D_{jmt}\left(p_{jmt}, p_{-jmt}\right). \tag{5}$$

The marginal cost mc_{jmt} is decomposed into a product-market effect ω_{jm} and a product-market-month specific shock ω_{jmt}:

$$mc_{jmt} = \omega_t + \omega_{jm} + \omega_{jmt}. \tag{6}$$

Stage 1. Entry and Product Decisions At the beginning of each year τ, each firm n is endowed with a set of potential products $\mathcal{J}_{n\tau}$. In the first stage, each firm decides on its set of products $\mathcal{J}_{nm\tau}$ in market m for the year τ to maximize the expected profit, which is the difference

[10] As mentioned in Section 2, we do not model retailer problems. On the technical side, this simplification allows us to avoid excessive computational burdens, especially in merger simulations. The underlying assumption is that efficient contracting resolves the double marginalization problem conditional on product entry. We show in Table 2 of Section 5.1 that our markup estimates are reasonable.

between the expected variable profit π_{nm} and the fixed cost C_{nm}:

$$\max_{\mathcal{J}_{nm\tau} \subseteq \mathcal{J}_{n\tau}} \pi_{nm} \left(\mathcal{J}_{nm\tau}, \mathcal{J}_{-nm\tau}\right) - C_{nm} \left(\mathcal{J}_{nm\tau}\right). \tag{7}$$

We now specify the expected variable profit and the fixed cost. We first make a timing assumption: when making product decisions, firms observe the product characteristics $\boldsymbol{x}_{jm}$, time fixed effects (ξ_t, ω_t), product-market characteristics (ξ_{jm}, ω_{jm}), and fixed costs for any product $j \in \mathcal{J}_{n\tau}$ and any firm n. After firms make product decisions, the month-to-month transient demand and marginal cost shocks $(\xi_{jmt}, \omega_{jmt})$ realize in the second stage. Given this timing assumption, the expected variable profit is the sum of expected values in (5) across the months in the year, and the expectation is taken over all $(\xi_{jmt}, \omega_{jmt})$.

The expected variable profit is the sum of the expected variable profit in (5) at the second-stage pricing equilibrium, where the sum is taken across the months in the year and the expectation is taken over the month-to-month transitory demand and marginal cost shocks $(\xi_{jmt}, \omega_{jmt})$. Specifically, let $\mathcal{J}_{-nm\tau}$ denote the set of products that firm n's competitors sell in market m and $p_{jmt}(\mathcal{J}_{nm\tau}, \mathcal{J}_{-nm\tau})$ be the second-stage equilibrium price for product j in the set $\mathcal{J}_{nm\tau}$ and month t in year τ, which depends on product characteristics, product-market fixed effects and transient shocks. Firm n's expected annual profit in (7) is, therefore,

$$\begin{aligned} &\pi_{nm} \left(\mathcal{J}_{nm\tau}, \mathcal{J}_{-nm\tau}\right) \\ = &\sum_{t=1}^{12} E_{\xi_{jmt}, \omega_{jmt}} \Bigg\{ \sum_{j \in \mathcal{J}_{nm\tau}} \left(p_{jmt}(\mathcal{J}_{nm\tau}, \mathcal{J}_{-nm\tau}) - mc_{jmt}\right) \\ &\cdot D_{jmt} \left(p_{jmt}(\mathcal{J}_{nm\tau}, \mathcal{J}_{-nm\tau}), p_{-jmt}(\mathcal{J}_{nm\tau}, \mathcal{J}_{-nm\tau})\right) \Bigg\}. \end{aligned} \tag{8}$$

The fixed cost function in (7) is specified as

$$C_{nm} \left(\mathcal{J}_{nm\tau}\right) = \sum_{j \in \mathcal{J}_{nm\tau}} \Big(\theta_0 + \theta_1 \text{craft}_j + \theta_2 (\text{in state})_j \cdot \text{craft}_j + \theta_3 (\text{in state})_j \cdot \text{craft}_j \cdot \text{dist}_{jm} + \zeta_{jm\tau}\Big), \tag{9}$$

where craft_j indicates whether the product is a craft beer, $(\text{in state})_j$ indicates whether product j is produced in California, and dist_{jm} is the distance between product j's brewery and market m. The specification is motivated by the evidence in Section 3 that distance matters for the in-state craft breweries, but not so much for the out-of-state ones. This is probably because the out-of-state breweries are much larger. Finally, the fixed cost shock $\zeta_{jm\tau}$ is assumed to be i.i.d. across j, m, τ and follows a normal distribution with mean 0 and standard deviation σ_ζ. In this specification, θ_1 measures the difference between craft and non-craft breweries in the fixed cost, θ_2 the difference between in-state and out-of-state craft breweries, and θ_3 the effect of distance on the fixed cost for the in-state craft breweries. This baseline specification of the fixed cost function rules out economies or dis–economies of scope. We extend the model to allow for this possibility in Appendix H.

5 Estimation

5.1 Estimation of Demand Parameters and Marginal Costs

We combine the aggregate data of product-market-level market shares and individual-level panel data of consumer purchases to estimate demand parameters. Specifically, we rely on the market share data to identify the mean price coefficient (α) and the fixed effect parameters (ξ_t, ξ_{jm}). The panel data and the correlations between household income and beer purchases help to identify the standard deviations of the unobservable consumer heterogeneity ($\sigma^{(\cdot)}$ parameters) and the effect of household income on consumer taste ($\kappa^{(\cdot)}$ parameters). We estimate these parameters using the Generalized Method of Moments approach where we combine a set of macro moments and two sets of micro moments.

To deal with the price endogeneity, the macro moments are based on the Hausman instrument V_{jmt}, which is the average price of product j in a "ring" consisting of markets more than 500KM from market m but less than 1000KM away.[11] The identifying assumption is

$$E\left(\xi_{jmt} \mid \boldsymbol{x}_j, V_{jmt}, t = 1, \ldots, 12\right) = 0.$$

We use these instruments to capture the large month-to-month variations in the ingredient costs (barley, malt, ...) and the heterogeneity in the proportions of these ingredients in different beers. Figure 2 shows the historical prices of barley and malt (in the units of per metric ton prices of barley and an index that linearly reflects the average prices of Malt and related products).

We next specify the micro moments. We construct the first set of micro moments to identify the standard deviation parameters $\sigma^{(\cdot)}$. Take σ^{craft} as an example. Intuitively, if the parameter σ^{craft} is large, a consumer's preference for craft products should be highly correlated across months, and therefore we should expect strong correlations of a consumer's purchase decisions across months. The implication is that conditional on a consumer ever purchasing a craft product, the consumer should purchase many craft products throughout the year if σ^{craft} is large.

We thus match the model predictions and the empirical counterparts of the following moments:

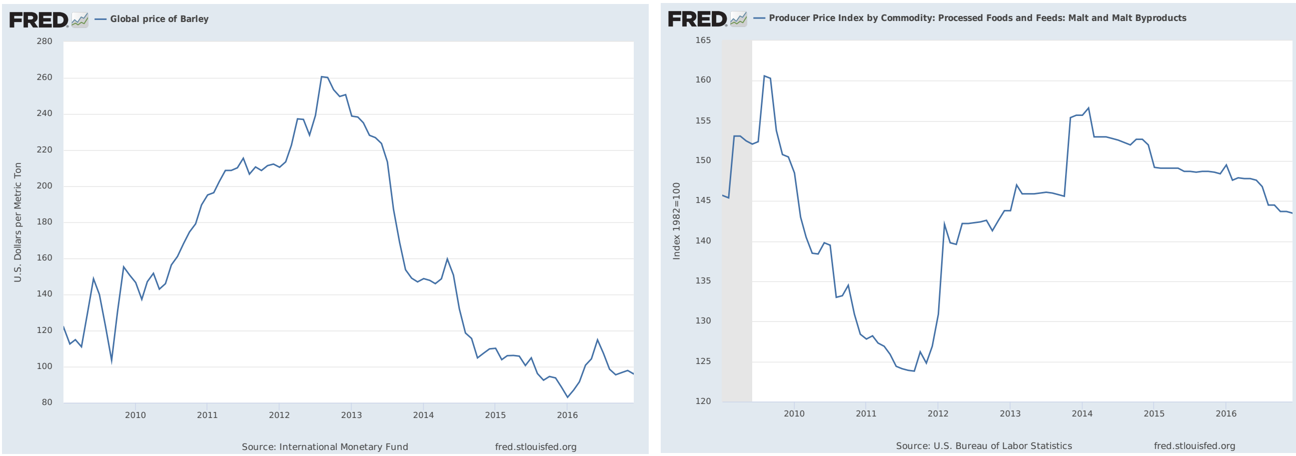
- A household i's expected annual purchase of a certain type of beer conditional on ever purchasing this type of beer in the year, i.e., $E\left(\sum_{t=1}^{12} q_{it}^f \mid \sum_{t=1}^{12} q_{it}^f > 0\right)$, where q_{it}^f is household i's total quantity of beer with a certain flavor (f = lager or f = light) or of a certain characteristic (f = import or f = craft) in month t. Matching these moments helps to identify

[11] To be precise, our instruments consist of variables $\left(\overline{p}_{jmt}, Z_{jmt}\right)$, where if j is available in the given "ring", $\overline{p}_{jmt}$ is the Hausman instrument and $Z_{jmt} = 0$. Otherwise $\overline{p}_{jmt} = 0$ and $Z_{jmt} = 1$. The results are robust to further increasing the distances or using the simple average or quantity-weighted average of prices.

Miller and Weinberg (2017) propose using the brewery–market distance as a price instrument. From our discussion in Section 3, distance may not be an excluded variable for craft beer demand. We thus include a product-market fixed effect, which absorbs the distance, in our demand model.

Figure 2: Prices of Barley and Malt

(a) Barley (b) Malt



σ^f.

- A household i's expected annual purchase of beer conditional on purchasing beer in the year, i.e., $E\left(\sum_{t=1}^{12} q_{it} \,|\, \sum_{t=1}^{12} q_{it} > 0\right)$, where q_{it} is household i's total beer purchase in month t. Matching this moment helps to identify σ_0.

We present the analytic expressions of these moments in Appendix A.

We also use a second set of micro moments that are helpful to identify the income effect on consumer tastes:

- The average price of the purchased beer among households whose income falls into a bin $\mathcal{I}$, i.e., $E\left(p_{j(i)mt} \,|\, y_i \in \mathcal{I}\right)$, where $p_{j(i)mt}$ is the price of the product purchased by household i in market m and month t, the income bins $\mathcal{I}$ are $(0, \$50K]$, $(\$50, \$100K]$ or $(\$100K, \$150K)$. Matching these moments helps to identify the income effect on price sensitivity κ_1.

- $E\left(\sum_{t=1}^{12} q_{it}^{\text{craft}} \,|\, \sum_{t=1}^{12} q_{it}^{\text{craft}} > 0, y_i \in \mathcal{I}\right)$, which helps to identify κ^{craft}.

- $E\left(\sum_{t=1}^{12} q_{it} \,|\, \sum_{t=1}^{12} q_{it} > 0, y_i \in \mathcal{I}\right)$, which helps to identify κ_0.

The estimation of the marginal costs is standard and follows Berry et al. (1995): we back out marginal costs based on the first-order condition of the profit maximization problem in (5).

5.2 Estimation of Fixed Cost Parameters

The fixed cost parameters include the parameters in the fixed cost function (i.e., $\theta_0, \theta_1, \theta_2, \theta_3$) and the standard deviation of the fixed cost shock (i.e., σ_ζ). To estimate these parameters, we develop a new method that relies on bounds of the conditional choice probability that a product is in the market. In Section 2, we have illustrated our bounds using a simple two-firm single-binary-decision model. In what follows, we present the bounds in our more general setting, explain the estimator, and describe implementation details. We provide additional details in Appendix C.

The construction of the bounds partly relies on the additive-separability of the fixed costs across products, which is a common assumption in the literature of estimating discrete games. In Appendix H, we extend our method for estimating fixed cost functions that allow for (dis–)economies of scope.

5.2.1 Bounds for the Conditional Choice Probability

To simplify the exposition, and also because we estimate the fixed cost parameters for each year separately, we suppress the subscript τ in the remainder of this section whenever it is clear, and we rewrite the profit function

$$\pi_{nm}\left(\mathcal{J}_{nm}, \mathcal{J}_{-nm}\right) - \sum_{j \in \mathcal{J}_{nm}} \left(\theta_0 + \theta_1 \cdot (\text{in state})_j + \theta_2 \cdot \text{craft}_j + \theta_3 (\text{in state})_j \cdot \text{craft}_j \cdot \text{dist}_{jm} + \zeta_{jm}\right)$$

as

$$\Pi_n(a_{nm}, a_{-nm}, X_m) - \sum_{j \in \mathcal{J}_n} a_{jm} \left[c(W_{jm}, \theta) + \zeta_{jm}\right],$$

where the vector X_m includes all relevant demand and marginal cost covariates (including the fixed effects) in market m, while the vector W_{jm} includes all fixed cost covariates. Moreover, we now use a vector of indicators a_{nm} to denote a firm's product portfolio $\mathcal{J}_{nm}$. Specifically, the length of a_{nm} equals the number of potential products that firm n is endowed with (i.e, the size of $\mathcal{J}_n$). The element of a_{nm} that corresponds to product $j \in \mathcal{J}_n$ (denoted by a_{jm}) is 1 if $j \in \mathcal{J}_{nm}$ and 0 otherwise. Furthermore, we use a_{-jm} to denote firm n's decision on its products other than j and the product choices of firm n's rival.

We define

$$\Delta_j(a_{-jm}, X_m) = \Pi_n(a_{jm} = 1, a_{-jm}, X_m) - \Pi_n(a_{jm} = 0, a_{-jm}, X_m) \tag{10}$$

to be the incremental change in firm n's expected variable profit when product $j \in \mathcal{J}_n$ is included in its product portfolio, given a_{-jm} and X_m. Given the discrete nature of a_{-jm}, the following minimum and maximum exist: $\underline{\Delta}_j(X_m) = \min_{a_{-jm}} \Delta_j(a_{-jm}, X_m)$ and $\overline{\Delta}_j(X_m) = \max_{a_{-jm}} \Delta_j(a_{-jm}, X_m)$.

Using these notations and letting A_{jm} represent the equilibrium product choice regarding product j in market m, the bounds in (3) for our illustrative model becomes[12]

$$
\begin{aligned}
& F\left(\underline{\Delta}_j(X_m) - c\left(W_{jm}, \theta\right), \sigma_\zeta\right) \\
\leq & \Pr\left(A_{jm} = 1 \mid X_{jm}, X_{-jm}, W_{jm}, W_{-jm}\right) \\
\leq & F\left(\overline{\Delta}_j(X_m) - c\left(W_{jm}, \theta\right), \sigma_\zeta\right).
\end{aligned} \tag{11}
$$

The identification of θ through these inequalities is similar to the idea of special regressors in entry games (Ciliberto and Tamer (2009); Lewbel (2019)): how A_{jm} varies with (X_{jm}, X_{-jm}) informs us about θ. For example, if the parameter σ_ζ is large, the upper and lower bounds would not co-vary strongly with the (X_m, W_m) and the inequalities in (11) are likely to be violated. For instance, if ζ_{jm} follows a symmetric distribution, both bounds in (11) approaches the constant 0.5 as σ_ζ approaches ∞. On the other hand, as σ_ζ is close to 0, both bounds simultaneously become close to 0 if $\overline{\Delta}_j(X_m) - c(W_{jm}, \theta) < 0$, or close to 1 if $\underline{\Delta}_j(X_m) - c(W_{jm}, \theta) > 0$ by the Chebyshev's inequality, potentially leading to violations of the inequalities in (11).

5.2.2 Identification and Inference

The identification of θ through inequalities in (11) is similar to the idea of special regressors in entry games (Ciliberto and Tamer (2009); Lewbel (2019)): how A_{jm} varies with (X_{jm}, X_{-jm}) informs us about θ. For example, if the parameter σ_ζ is large, the upper and lower bounds would not co-vary strongly with the (X_m, W_m) and the inequalities in (11) are likely to be violated. For instance, if ζ_{jm} follows a symmetric distribution, both bounds in (11) approaches the constant 0.5 as σ_ζ approaches ∞. On the other hand, as σ_ζ is close to 0, both bounds simultaneously become close to 0 if $\overline{\Delta}_j(X_m) - c(W_{jm}, \theta) < 0$, or close to 1 if $\underline{\Delta}_j(X_m) - c(W_{jm}, \theta) > 0$ by the Chebyshev's inequality, potentially leading to violations of the inequalities in (11).

Based on the inequalities in (11), we define the moment functions as

$$
\begin{aligned}
L(X_{jm}, X_{-jm}, W_{jm}, W_{-jm}, \theta, \sigma_\zeta) &= F\left(\underline{\Delta}_j(X_m) - c(W_{jm}, \theta), \sigma_\zeta\right) - \Pr\left(A_{jm} = 1 \mid X_{jm}, X_{-jm}, W_{jm}, W_{-jm}\right), \\
H(X_{jm}, X_{-jm}, W_{jm}, W_{-jm}, \theta, \sigma_\zeta) &= \Pr\left(A_{jm} = 1 \mid X_{jm}, X_{-jm}, W_{jm}, W_{-jm}\right) - F\left(\overline{\Delta}_j(X_m) - c(W_{jm}, \theta), \sigma_\zeta\right).
\end{aligned}
$$

To simply notations, let $X_{jm} = (X_{jm}, W_{jm})$ represent all observable covariates and $\theta = (\theta, \sigma_\zeta)$ all fixed-cost parameters. We collect the above moment functions as

$$
h(X_{jm}, X_{-jm}, \theta) = (L(X_{jm}, X_{-jm}, \theta),\ H(X_{jm}, X_{-jm}, \theta))'.
$$

Then, the bounds imply the following conditional moment conditions:

$$
E(h(X_{jm}, X_{-jm}, \theta) \mid X_{jm}, X_{-jm}) \leq 0.
$$

[12]In the multi-binary decision game, the assumption needed for the bounds becomes as follows: A_{jm} is not a dominated strategy in the sense that $1 - A_{jm}$ does not always lead to a higher profit for j's firm than A_{jm} (no matter what a_{-jm} is).

We follow Chernozhukov et al. (2007) and Andrews and Shi (2013) to construct the confidence set for the true values of the parameters and report results from both methods. More details on inference are provided in Appendix C.

5.2.3 Empirical Implementation

To compute the sample analog of the moments, we need to compute $\underline{\Delta}_j(X_m)$ and $\overline{\Delta}_j(X_m)$ and estimate the conditional choice probability $\Pr(A_{jm} = 1 \mid X_{jm}, X_{-jm})$. We lay out the steps here.

As a reminder, $\underline{\Delta}_j(X_m) = \min_{a_{-jm}} \Delta_j(a_{-jm}, X_m)$ and $\overline{\Delta}_j(X_m) = \max_{a_{-jm}} \Delta_j(a_{-jm}, X_m)$. Directly solving for the minimum and the maximum of the expected profits over all possible values of a_{-jm} is computationally costly, because there are $2^{\text{length of } a_{-jm}}$ possible values of a_{-jm} and computing $\Delta_j(a_{-jm}, X_m)$ for each a_{-jm} involves solving stage-2 price games for multiple simulated draws of demand and marginal cost shocks. However, economic intuition suggests that because products are substitutes, we can approximate the minimum by

$$\underline{\Delta}_j(X_m) \approx \Delta_j((1, ..., 1), X_m)$$

and the maximum by

$$\overline{\Delta}_j(X_m) \approx \Delta_j((0, ..., 0), X_m).$$

These approximate extrema are exact for the model in Ciliberto and Tamer (2009), where the variable profit function is a linear function of and is decreasing in the entry decisions of other products. For more general demand and pricing models such as ours, we conduct Monte Carlo simulations and find the approximate extrema also coincide with the true ones across a variety of parameter specifications (see Appendix F).

As mentioned in Section 2, the tightness of our bounds depends on the gap between $\underline{\Delta}_j(X_m)$ and $\overline{\Delta}_j(X_m)$. We plot the histogram of the ratio $\underline{\Delta}_j(X_m)/\overline{\Delta}_j(X_m)$ across all market–potential product pairs in Figure 3. A smaller ratio reflects a larger difference between the lower and upper bounds. The ratios for the majority of the market-product pairs are around 0.3 to 0.7.

To calculate $\underline{\Delta}_j((\cdot), X_m)$ and $\overline{\Delta}_j((\cdot), X_m)$ for each potential product in each market, we solve for the corresponding stage-2 pricing equilibrium based on the estimated demand and marginal costs. For the demand and marginal cost estimation, we try to be general and include the product-market fixed effects ξ_{jm} and ω_{jm} to capture systematic variations at the product-market levels. However, this specification does not directly give us ξ_{jm} or ω_{jm} when j is not observed in market m. Therefore, at this stage of estimation, we impose more structures and decomposes ξ_{jm} into a product fixed effect, a market fixed effect and a linear combination of market-product specific variables, which are indicators based on the distance from j's brewery to the market m following the motivation in Section 3. Appendix B provides the detailed estimation procedure and evidence that our approach has reasonably good in-sample and out-of-sample fit.

We use a nearest-neighbor approach to estimate the empirical distribution $\Pr(A_{jm} = 1 \mid X_{jm}, X_{-jm})$. Appendix C provides details on this procedure. By using empirical estimates of conditional choice

Figure 3: Tightness of the Bounds: Histogram of $\underline{\Delta}_j(X_m)/\overline{\Delta}_j(X_m)$

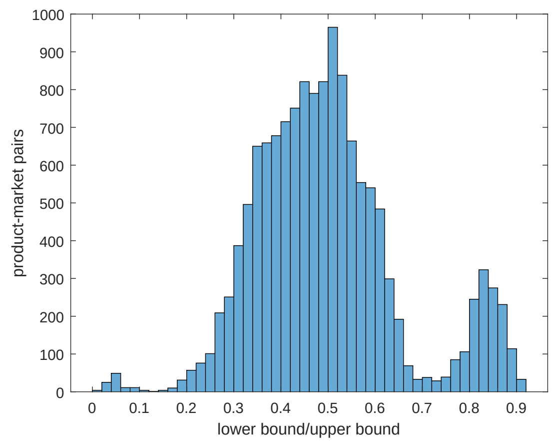


Table 1: Demand Estimates

unobs. heterogeneity	σ_0	0.32	income effect	κ_0	-6.89
		(0.05)			(0.02)
	σ^{lager}	0.25		κ^{craft}	0.54
		(0.09)			(0.01)
	σ^{light}	6.67		κ_α	0.37
		(0.01)			(0.00)
	σ^{craft}	4.68			
		(0.01)	mean price coef.	α	-0.60
	σ^{import}	0.88			(0.01)
		(0.00)			

probabilities and conditional moment inequalities, our method bears some semblance to the CCP approach in the estimation of dynamic models (Bajari et al. (2007)).

6 Estimation Results

We report our estimation results using the 2016 data. Results are available for other years.

Demand estimates are reported in Table 1. The estimates indicate significant heterogeneity in preferences. In particular, although high-income households are less likely to purchase beer ($\hat{\kappa}_0 < 0$), conditional on a purchase, they are less price sensitive ($\hat{\kappa}_\alpha < 0$) and prefer craft products $\left(\hat{\kappa}^{\text{craft}} > 0\right)$. To see the substitution between craft and non-craft beers, we calculate the own and cross elasticities among the top-5 non-craft brands and top-5 craft brands in 2016 (see Table 2).[13] We find that the substitution within craft brands is much larger than those across the two groups.

[13]Per data contract with Nielsen, we refrain from discussing the specific identities of beers or breweries in the data.

Table 2: Elasticities: Top-5 Main Brands and Top-5 Craft Brands

	Main Brands					Craft Brands					Markup ($)
Main Brands	-2.18	0.77	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.00	4.49
	0.80	-2.21	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.00	4.48
	0.01	0.01	-5.18	0.06	0.06	0.00	0.01	0.00	0.00	0.00	2.67
	0.01	0.01	0.07	-5.26	0.06	0.00	0.01	0.00	0.00	0.00	2.72
	0.02	0.02	0.11	0.09	-3.89	0.01	0.01	0.01	0.00	0.00	2.22
Craft	0.00	0.00	0.03	0.02	0.02	-4.52	0.26	0.26	0.11	0.07	3.94
	0.00	0.00	0.02	0.02	0.02	0.26	-4.53	0.26	0.12	0.08	3.80
	0.00	0.00	0.02	0.02	0.01	0.23	0.26	-4.54	0.11	0.08	3.73
	0.00	0.00	0.02	0.02	0.01	0.23	0.28	0.25	-4.68	0.08	3.92
	0.00	0.00	0.02	0.02	0.01	0.23	0.27	0.25	0.11	-4.66	3.63

We back out marginal costs using the first-order condition in the pricing stage of the game. The markup estimates of the top products (quantity-weighted average across markets where the product is available) are reported in the last column of Table 2. In 2016, the median markup is \$2.99, and the median craft markup is \$3.89. All terms are 2016 dollars.

To estimate the fixed cost parameter, we define the set of firm n's potential products in year τ, $\mathcal{J}_{n\tau}$, as $\mathcal{J}_{n\tau} = \{j : j \text{ is owned by firm } n \text{ and } j \text{ is in any market in year } \tau \text{ in our sample}\}$. Given our focus on craft products and the very small cross-elasticity between the craft and other products (Table 2), at this stage of estimation, we keep in our sample craft products and the non-craft products by Blue Moon (owned by MillerCoors) and Shock Top (owned by ABI).[14] Despite not being designated as craft by the Brewers Association, the packaging and marketing of Blue Moon brands are allegedly similar to craft products (Field (2019)), and ABI introduced Shock Top brands to compete with Blue Moon (Shears (2014)). Including these products allows us to estimate the parameter of the indicator of whether a product is craft. Moreover, we focus on markets where at least one craft product was observed. These restrictions still leave us with a large number of observations for estimation. In 2016, there are 95 potential products, 149 markets and 14,155 product-market combinations.

We report the 95% confidence set projected to each parameter from the 2016 data in Table 3. All estimates are in 2016 US dollars. The projection of the confidence set following CHT is slightly shifted and narrower compared to that following AS. The projected 95% confidence interval of the fixed cost intercept θ_0 based on CHT ranges from \$2,075 to \$3,139, and that based on AS ranges from \$2,230 to \$4,336. To put the figures in context, we note that the change in the expected variable profit $\Delta_j(a_{-jm}, X_m)$ in the estimation sample has a mean of 3,755 dollars and a standard deviation of 12,925 dollars in 2016. The positive projected confidence interval for the parameter θ_1 indicates a higher fixed cost for craft products. The parameter θ_2 captures the difference between

[14] In our sample period, Goose Island and a few other craft products were acquired by large breweries such as ABI, and the Brewers Association removed their "craft" designations. We continue to designate these products as craft but assume their acquirers set their prices. The underlying assumption is that consumers base purchase decisions on tastes: the craft beers are still produced from the same facilities and we assume the chemical compositions remain the same as the pre-merger products.

Table 3: Estimates of Fixed Costs: Projected 95% Confidence Intervals, 2016

	CHT	AS
Constant (θ_0)	[2075.12, 3139.05]	[2250.49, 4336.24]
Craft (θ_1)	[1102.09, 2076.87]	[616.18, 2932.42]
In State× Craft (θ_2)	[-1173.51, 437.03]	[-2118.48, 627.42]
Distance^a×In State× Craft (θ_3)	[1216.18, 3451.17]	[770.51, 5529.83]
Std. Dev. (σ_ζ)	[1313.70, 2303.08]	[1302.35, 4059.56]

^{a}: Distance in 1000KM

in-state and out-of-state craft beer fixed costs, which have a relatively wide projected confidence interval. The result on the distance parameter θ_3 shows that the in-state craft breweries' costs increase in the distance from the brewery to the market. The estimation results also indicate sizable variance of the unobserved fixed cost shock. The estimate of the standard deviation of the unobserved shocks is of comparable magnitude to the average fixed cost, which is around 4500 to 5000 dollars.

7 Counterfactual Results

7.1 Counterfactual Designs

Using the estimated model, we consider a counterfactual merger where the largest firm in our sample (a "macro" brewery) acquires 3 largest craft firms (excluding Boston Beer Company and Sierra Nevada Brewing, which are unlikely merger targets given their sizes) in 2016. We simulate the merger in 149 markets where at least one craft product is observed in data. Through the acquisition, the large brewery would have acquired more than 50% of the craft beer shares in about half of the markets. The merger may raise prices, providing incentives for incumbent product adjustment and new firm entry. We allow firms to change their craft products and craft breweries to enter or exit. We hold the non-craft product choices fixed as observed in data to ease the computation burden, but we allow their prices to adjust. The simplification is justified by the estimated small substitution between the craft and non-craft products.

There are three types of shocks in the models: demand, marginal cost and fixed cost shocks. We draw demand and marginal cost shocks directly from their estimated distributions (Appendix B) to calculate the expected variable profits given product choices ($\pi_{nm}(\mathcal{J}_{nm}, \mathcal{J}_{-nm})$ in (7)). As for fixed cost shocks, we draw from the estimated distribution while taking into account selection. In other words, our fixed cost draws are consistent with the observed pre-merger equilibrium, which is important to ensure that the per- and post-merger outcomes are comparable (Details on how we draw fixed cost shocks can be found in Appendix D).

In the simulation, a decision maker (or a potential entrant) is a firm that is observed in any market in our sample. Each firm is endowed with a set of potential products, consisting of the firm's craft products observed in the sample. In each market, a firm chooses a subset from its potential products. Choosing a non-empty subset implies entry into the market. The merging firms choose products from the union of the sets of their potential products. We compute the post-merger product equilibrium using the algorithm in Fan and Yang (2020). Additional computational and simulation details are in Appendix E.

In addition to the counterfactual simulation described above (CF1) where we allow for three adjustment margins – new firm entry, product adjustment and price adjustment, we conduct two more counterfactual simulations to decompose the importance of each margin. In CF2, we allow for only the latter two adjustment margins (incumbent product adjustment and price adjustment) by removing products added by new entrants in CF1 and recompute the pricing equilibrium. In CF3, we allow for only the price effect of the merger by restoring the products in the market to those in the pre-merger market 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 adjustment (CF2 - CF3).

7.2 Counterfactual Results

7.2.1 Heterogeneous Merger Outcomes Across Markets

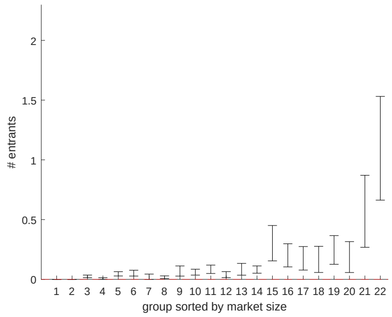
For simulations, we use the point estimates of the demand and marginal cost parameters and sample 15 parameter vectors from the estimated confidence set following the AS approach for the fixed cost parameters. In what follows, we present how the range (across parameter values) of the average merger effects (averaged across simulation draws of the shocks) vary across markets. To this end, for each market and each fixed cost parameter vector, we compute the average simulated merger effects across the simulation draws of the shocks. We then further take the (market size weighted) average across markets of similar sizes for the purpose of presentation. Specifically, we sort our 149 simulated markets according to their market sizes, group them from small to large into 22 groups (with 7 markets in the first 21 groups and the largest two markets in the last group). Finally, in Figure 4 and subsequent figures, for each group of markets, we present the projected 95% confidence interval (the maximum and minimum average simulated merger effects within a market group across sampled parameters from the confidence set) of the counterfactual outcomes.

Figure 4 shows that new entry happens in most markets (panel (a)) and these new entrants bring in new products (panel (b)). Both the number of entrants and the number of new products added by them increase with market size. As for incumbents, the merging firms always drop products (panel (c)) while the non-merging firms add products in most markets (panel (d)). However, the net change in the number of products by the incumbents is always negative except in the last group of markets, which has the largest market size (panel (e)). Even considering the added products by new entrants, the overall number of products decreases except in the largest several markets (panel (f)). The increase in the quantity-weighted average craft prices is centered around 15 cents (panel (g)).

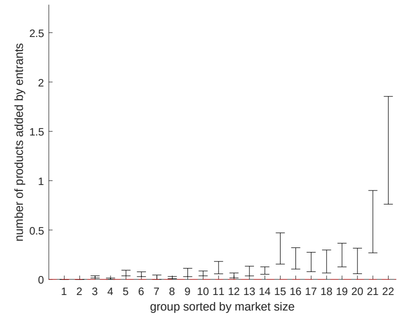
Figure 5 presents the effect of the merger on consumer welfare. Panel (a) shows the changes of

Figure 4: Product Variety, Entry and Prices

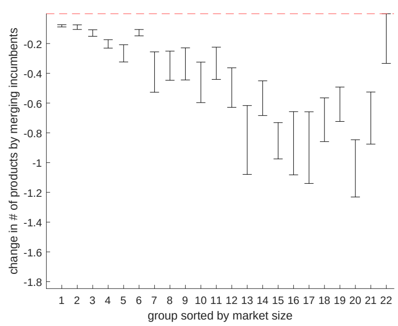
(a) Number of Entrants



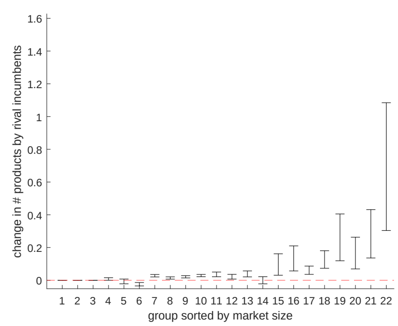
(b) Number of Products Added by Entrants



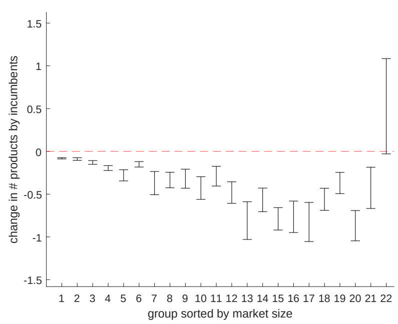
(c) Change in the Number of Products by Merging Firms



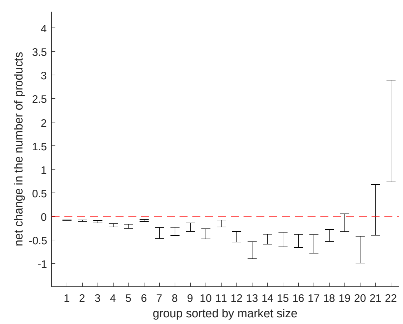
(d) Change in the Number of Products by Incumbent Non-merging Firms



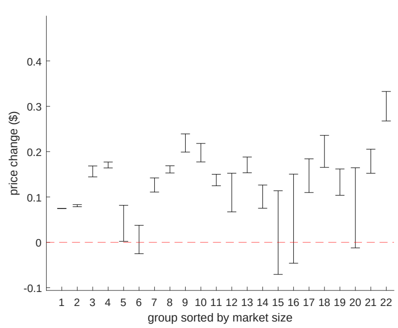
(e) Change in the Number of Products by Incumbent



(f) Change in the Number of Products



(g) Change in Craft Prices



average consumer surplus, which is defined as the change of consumer surplus in a market divided by its total annual alcohol sales. The average consumer surplus ranges from close to 0 to -0.3 dollars. For the pre-merger craft consumers, however, the average consumer surplus loss is the range of -10 and -35 dollars (Panel (b)).[15] In panel (c), we break out the average consumer welfare effect attributed to the variety changes and find that the product variety effect of the merger recovers some consumer surplus loss in the larger markets, but is either ambiguous or exacerbates the negative price effects in smaller markets. A further decomposition of the product variety effect on consumer welfare indicates that the product variety effect due to new entry is positive (panel (d)) but, consistent with the product changes, often offset by the product variety changes of the incumbents (panel (e)).

7.2.2 Correlation between the Merger Effects and Market Characteristics

The heterogeneity of the merger effects on product variety and welfare is associated with heterogeneity in market characteristics. For example, if the products of the merging firm are close substitutes, the merged firm is more likely to drop some products and increase prices significantly. At the same time, pronounced price increases attract firm entry and product entry by non-merging firms. Therefore, a measure of the merging firms' market power may be positively correlated with both the number of dropped products by the merging firms and the added products by other firms, although the sign is less clear with the net change of the number of products. Furthermore, high fixed costs should be associated with a smaller increase or a larger decline in the number of products. In addition, everything else equal, we should expect more entry in larger markets.

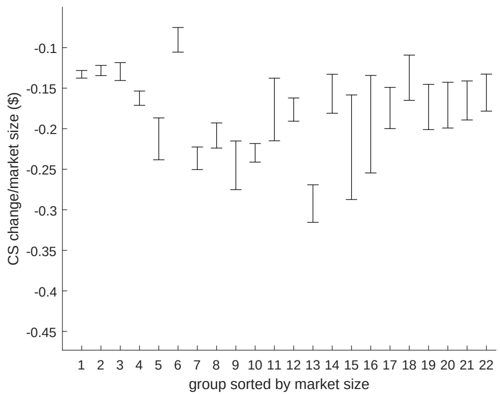
We use regression analysis to document the correlation between the merger effects on product variety and welfare with these market characteristics. One observation in the regression is a market. For each market, we measure the merging firms' market power in the market by the increase in the quantity-weighted average price of their products in CF2 (i.e., the price adjustment only counterfactual simulation). We measure the average fixed cost of the merging firms in a market by the average of the fixed cost of all their potential products, where the fixed cost of product j is given by $C(W_{jm}, \hat{\theta})$. In other words, the average fixed cost does not include the mean-zero unobservable fixed costs and thus reflect the features of the products and the distance between breweries and the markets. The average fixed costs of other firms is defined analogously.

We regress the changes in the numbers of products by merging firms (so dropping products corresponds with a negative change), by other firms and the net change in a market on our measure of market power, mean fixed costs and market sizes. We carry out the regressions for each sampled fixed cost parameter values in the confidence set and report the range of the parameters estimates in Table 4. The signs in columns (a) and (b), corresponding with the changes in the number of products by merging firms and other firms, are consistent with the discussions in Section 7.2. The estimates are significant at 5% level for all parameters in the confidence set for variety-fixed price increases in columns (a) and (b), and significant for the fixed costs in column (b). In column (d),

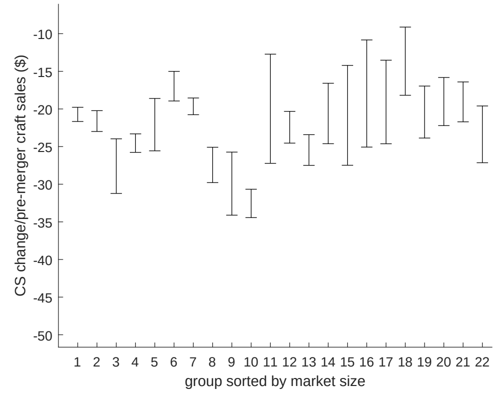
[15] We calculate the figures by dividing the total consumer welfare loss by the quantity of pre-merger craft products.

Figure 5: Average Consumer Surplus

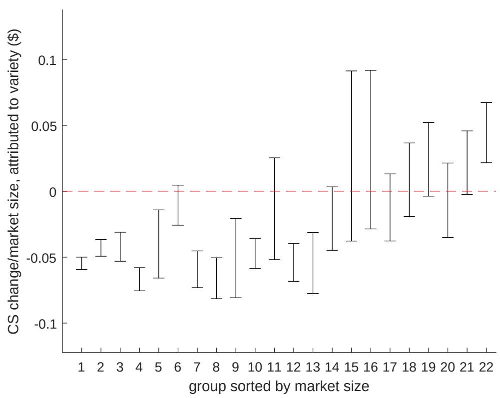
(a) Change in the Average Consumer Surplus



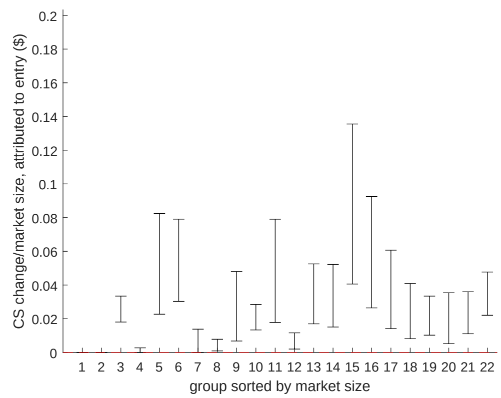
(b) Change in the Average Craft Consumer Surplus



(c) Change in the Average Consumer Surplus Attributed to Variety



(d) Change in the Average Consumer Surplus Attributed to Entry



(e) Change in the Average Consumer Surplus Attributed to Incumbent Adjustment

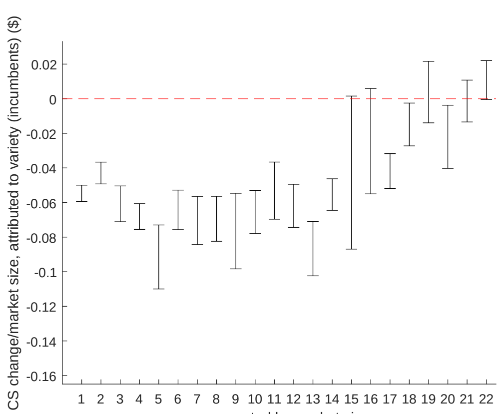


Table 4: Changes in the Number of Products[a]

	(a) Merging Firms	(b) Other Firms	(c) Other Firms	(d) Market	(e) Market
average price increase, merging firms ($), variety fixed	[-2.82, -1.93]*	[0.27, 0.68]*	[0.30, 0.70]*	[-2.15, -1.40]*	[-2.16, -1.38]*
average fixed cost ($1000), merging firms	[-0.68, -0.12]			[-0.63, -0.05]	[-0.64, 0.01]
average fixed cost ($1000), other firms		[-1.32, -0.32]*	[-1.32, -0.32]*	[-1.74, -0.31]	[-1.74, -0.40]
average household income ($10,000)			[-0.01, 0.01]		[-0.03, 0.01]
market size (10^6)	[-0.07, 0.08]	[0.16, 0.48]*	[0.16, 0.48]*	[0.09, 0.57]*	[0.09, 0.57]*
R^2	[0.28, 0.33]	[0.62, 0.76]	[0.62, 0.76]	[0.19, 0.42]	[0.20, 0.42]
N	149	149	149	149	149

[a] Linear regressions where the dependent variables are the changes in the numbers of products by merging firms and other firms and the net change in a market. Each observation is a market. We report the range of estimates from the parameters in the confidence set. * indicates significance above 95% confidence level for all parameters in the sampled confidence set.

the correlation between our measure of market power and the number of products is weaker than (a) and (b), reflecting the countervailing nature of how market power both induces product entry and causes the merging firms to drop products. The sign is negative, indicating that market power is correlated with a net decrease in the number of products. In the three regressions, fixed costs are correlated with a reduced number of products. We also note that market sizes are positively correlated with product entry. In columns (c) and (e), we also control for the average income of the county of the market, which does not appear to be correlated with the changes in variety. Finally, the measure of market power and average fixed costs account for a significant portions of variations in the changes of the number of products. By regressing the dependent variables on just market sizes, the R^2s drop to $[0.01, 0.09]$, $[0.59, 0.72]$ and $[0.00, 0.26]$ for columns (a), (b) and (d), respectively.

7.2.3 Aggregate Merger Effects

Having established the heterogeneity in the merger effects across markets and documenting the correlation between the merger effects and market characteristics, we now turn to the aggregate merger effects across the simulated 149 markets. Similar to Section 7.2.1, we again report the range (across parameter values) of the average merger effects (averaged across simulation draws of the shocks for each parameter value).

In the left panel for Rows (1)–(9), we report the weighted average across markets where the weights are the market sizes. In the right panel for Rows (10)–(20), we report the sum. The 95% confidence interval of the (weighted) average number of expected new entrants is $[0.2, 0.6]$. On average, the merged firms drop between 0.5 to 0.7 products, while the rival incumbents add 0.1 to 0.4 products and new entrants adds 0.2 to 0.7 products. The average beer prices are barely affected, but the merger increases the craft prices by about 15 cents. In comparison, if the variety is held fixed, the average craft price increases by 22 cents (not reported in Table 5). The average price of the merging firms increases by about 40 cents. The decrease in quantity and increase in prices lead to a total welfare loss ranging from 1.4 to 1.8 million dollars, aggregated across the simulated markets. With entry and incumbent product adjustment, the profit of the merging firms changes

Table 5: Aggregate Post-Merger Outcomes

Average Change Per Market			Aggregate Change Across Markets		
(1)	# of firms	[-2.7, -2.3]	(10)	quantity (1000)	[-325.8, -255.8]
(2)	# new entrants	[0.2, 0.6]	(11)	craft	[-302.7, -224.8]
(3)	# of products	[-0.3, 0.4]	(12)	craft, merging firms	[-429.4, -413.1]
(4)	merging firms	[-0.7, -0.5]	(13)	consumer surplus ($1000)	[-1826.0, -1370.3]
(5)	non-merging incumbents	[0.1, 0.4]	(14)	craft beer profits ($1000)	[192.4, 307.7]
(6)	new entrants	[0.2, 0.7]	(15)	merging firms	[-3.1, 53.8]
(7)	average price ($)	[0.0, 0.0]	(16)	total surplus ($1000)	[-1518.2, -1175.5]
(8)	craft products ($)	[0.1, 0.2]	ΔCS decomposition ($1000)		
(9)	craft, merging firms ($)	[0.4, 0.4]	(18)	due to variety change	[-162.4, 293.3]
			(19)	due to entry	[124.2, 385.0]
			(20)	due to incumbent product adjustments	[-286.6, -69.4]

from -3,100 to 53,800 dollars. If the variety is held fixed, the profit increase would be 65,200 dollars (not reported in Table 5), indicating that entry and product adjustment curb the profitability of the merger. The net effect of incumbent product adjustments exacerbates the average consumer surplus loss by 69,400 to 286,600 dollars while entry recovers 124,200 to 385,000 dollars, resulting in a net change of -162,400 to 293,300 dollars of consumer welfare due to product variety changes, with the magnitude being at most 20% of eventual consumer welfare loss.

We conducted two robustness analyses. In Appendix G, we allow the mean and the standard deviation of the fixed costs to differ across market sizes. In Appendix H, we estimate a fixed cost function that allows for (dis–) economies of scale. For each robustness analysis, we re-estimate the fixed cost parameters and repeat the counterfactual simulations. In the first analysis, we find that the intercepts and variances of the fixed costs increase with market sizes. In the second, we find dis–economies of scale. In both cases, our counterfactual results are robust.

8 Conclusion

We develop a new method to estimate multiple-discrete choice games where firms decide on entry and product choices. We apply the method to study the effects of merger on firm entry, product choices and prices in the retail craft beer market in California. We make two contributions. On the methodological front, our method combines the ideas of conditional choice probabilities and conditional moment inequalities. By constructing bounds for a single action's probability instead of the probability of a game's outcome, our estimator is easy to compute and scalable to large games (where there are many firms and/or when each firm makes a long vector of binary decisions). On the substantive front, the paper adds to the literature of merger and endogenous product choices. For the retail craft beer market in California, we find significant heterogeneity in merger outcomes across markets. Large markets are likely to see post-merger product entry and firm entry that partially offset the consumer surplus loss from increased prices, but in a majority of markets, the net number of products decreases, which tends to further reduce consumer welfare. Aggregated across markets, the effects of entry and product variety are positive but account for a minor part of consumer surplus.

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A Details on Micro-Moments

In this section, we explain how the micro-moment $E\left(\sum_{t=1}^{12} q_{it}^f \mid \sum_{t=1}^{12} q_{it}^f > 0\right)$ explained in Section 5.1 is computed. The calculation of the model implication of other micro-moments is similar. The moment $E\left(\sum_{t=1}^{12} q_{it}^f \mid \sum_{t=1}^{12} q_{it}^f > 0\right)$ is the average annual purchase of a household of a certain type of beer conditional on ever purchasing this type of beer in the year, where q_{it}^f is household i's quantity of beer with a certain flavor (f = lager or f = light) or of a certain characteristic (f = import or f = craft) in month t.

Let $\tilde{s}_{jmt}(\boldsymbol{\nu}, y)$ denote the Logit choice probability of product j when the vector of unobserved tastes and income are $(\boldsymbol{\nu}, y)$ and $G_m(\boldsymbol{\nu}, y)$ denote the distribution of the unobserved preferences and income, which can vary across markets and is thus indexed by m. We first compute the conditional mean in each market m: $E\left(\sum_{t=1}^{12} q_{it}^f \mid \sum_{t=1}^{12} q_{it}^f > 0, m\right)$. We assume that each consumer has $R = 8$ opportunities per month to buy beer (where on each trip the consumer buys 1 or 0 products), which is the average number of trips to the stores per household in the Nielsen Consumer Panel data .[16] Then, the probability of purchasing at least one beer of type f in market m conditional on $(\boldsymbol{\nu}, y)$ is

$$\tilde{\rho}_m^f(\nu, y) = 1 - \prod_t \left(1 - \sum_{j \text{ s.t. } x_j^f = 1} \tilde{s}_{jmt}(\boldsymbol{\nu}, y)\right)^R,$$

where the summation $\sum_{j \text{ s.t. } x_j^f=1}$ is the sum over all products in the choice set in market m, month t where the product is of type f. Therefore, the expected total quantity of purchase conditional buying f at least once in market m is

$$E\left(\sum_{t=1}^{12} q_{it}^f \mid \sum_{t=1}^{12} q_{it}^f > 0, m\right) = \int_{\boldsymbol{\nu}, y} \frac{R \sum_{j \text{ s.t. } x_j^f=1} \tilde{s}_{jmt}(\boldsymbol{\nu}, y)}{\tilde{\rho}_m^f(\nu, y)} dG_m(\boldsymbol{\nu}, y).$$

[16] The demand estimates are robust to $R = 5, 6, 7$.

. To obtain the average across markets, we weigh these conditional means in each market by the expected number of households who purchases products of type f at least once. We define the unconditional probability of purchasing at least once beer of type f as

$$\rho_m^f = \int \tilde{\rho}_m^f (\nu, y)\, dG_m (\boldsymbol{\nu}, y) \,,$$

which implies the total number of households that purchase at least one product of type f in market m is $O_m \cdot \rho_m^f$, where O_m is the market size of m. Therefore, the expected purchase of type f conditional on having at least one purchase of type f is

$$E\left(\sum_{t=1}^{12} q_{it}^f \mid \sum_{t=1}^{12} q_{it}^f > 0\right) = \frac{1}{\sum_m O_m \cdot \rho_m^f} \cdot \left(\sum_m E_i\left(\sum_{t=1}^{12} q_{it}^f \mid \sum_{t=1}^{12} q_{it}^f > 0, m\right) \cdot O_m \cdot \rho_m^f\right).$$

B Details on Computing $\Delta_j(X_m)$

This section discusses how to compute the incremental variable profit $\Delta_{jn}(a_{-jm}, X_{nm})$ in (10), which is the change in variable profits of firm n when product j is added to market m. Given a_{-jm} and X_{nm}, one can compute

$$\Delta_{jn}(a_{-jm}, X_{nm}) = \pi_{nm}(\mathcal{J}_{nm\tau} \cup j, \mathcal{J}_{-nm\tau}) - \pi_{nm}(\mathcal{J}_{nm\tau} \cup j, \mathcal{J}_{-nm\tau})$$

using (8), where $(\mathcal{J}_{nm\tau}, \mathcal{J}_{-nm\tau})$ is the set of products in the market corresponding with $(a_{jm} = 0, a_{-jm})$. We therefore focus on how to estimate X_{nm}, the vector of all relevant demand and marginal cost covariates. The vector consists of the following components:

$$X_{nm} = \left\{\left(\xi_{\tilde{j}m}, \omega_{\tilde{j}m}, \boldsymbol{x}_{\tilde{j}}\right)_{\tilde{j}:a_{\tilde{j}m}=1}, G_m(\boldsymbol{\nu}, y)\right\},$$

where $G_m(\boldsymbol{\nu}, y)$ is the market specific distribution of unobserved tastes and income. The observables $\boldsymbol{x}_{\tilde{j}}$ are given in data, and $G_m(\boldsymbol{\nu}, y)$ given by the demand estimates. The rest of the section concerns the estimation of the demand and marginal cost unobservables ξ and ω.

In the demand estimation, we estimate ξ_t as parameters, and the inversion following Berry et al. (1995) allows us to estimate $\hat{\xi}_{jm}$ for observed product-market combination jm. To estimate $\Delta_{jn}(a_{-jm}, X_{nm})$ such that j is not observed in m, we further parameterize $\xi_{jm} = \xi_j + \xi_m + \gamma Z_{jm}$, where γ is a vector of parameters and Z_{jm} is a vector of product-market specific observables. In practice, we construct Z_{jm} as indicators of whether the distance is in the bins of 0–50KM, 50–150KM, 150–300KM, 300–600KM, 600–1200KM, and greater than 1200KM. We define μ_{jmt} as the inverted mean utility net of the time fixed effects from the Berry inversion

$$\mu_{jmt} = \xi_{jm} + \xi_{jmt}.$$

We then estimate (ξ_j, ξ_m, γ) as parameters from the regression

$$\mu_{jmt} = \xi_j + \xi_m + \gamma Z_{jm} + \xi_{jmt},$$

and construct ξ_{jm} from the parameter estimates $\hat{\xi}_j + \hat{\xi}_m + \hat{\gamma} Z_{jm}$. We can similarly construct ω_{jm}.

To simulate the expected profit in (10), we use the empirical distribution of the residuals $\left(\hat{\xi}_{jmt}, \hat{\omega}_{jmt}\right)$ from the estimating equations above. The identification of price coefficients relies on the assumption that product choices are uncorrelated with the transient shocks $(\xi_{jmt}, \omega_{jmt})$. This assumption also is sufficient for the consistency of the procedures above.

We next show that $(\xi_{jmt}, \omega_{jmt})$ accounts for a small proportion of the variations in mean utility and marginal costs. Specifically, we examine the in-sample and out-of-sample fits. We randomly sample a percentage ρ of the entire demand data (at the product-market-month level). This is our training sample. We estimate the regression above, and then calculate the R^2 as a measure of in-sample fit. We then use the estimates to predict μ_{jmt} and mc_{jmt} on the other $1 - \rho$ sample. For example, the prediction of μ_{jmt} is

$$\hat{\xi}_j + \hat{\xi}_m + \hat{\gamma} Z_{jm},$$

where we assume the predicted value of the transient shock ξ_{jmt} is 0. If the prediction involves a j or m whose ξ_j, ξ_m values are not estimated, we also set these values to 0. The prediction error is

$$\mu_{jmt} - \left(\hat{\xi}_j + \hat{\xi}_m + \hat{\gamma} Z_{jm}\right).$$

We calculate an "out-of-sample" R^2, which is 1 minus the variance of the prediction errors divided by the variance of the corresponding outcome variables.

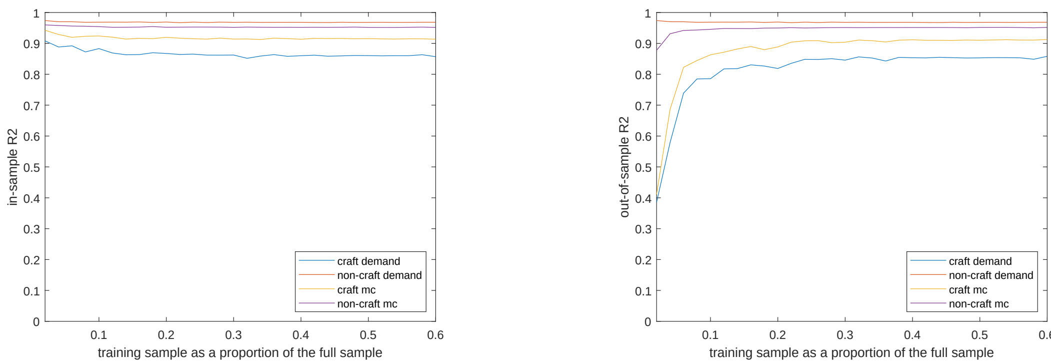
We estimate the models for craft and non-craft separately, allowing for different estimates of ξ_m and γ for craft and non-craft products. The craft products account for 31424 of 111219 observations in 2016. Using the 2016 estimates, we plot the in- and out-of- sample fit of μ_{jmt} and mc_{jmt}, where the size of the training data is a proportion of ρ of the full sample, in Figure B.1 (a) and (b) as ρ varies from 0.01 to 0.6. The in-sample R^2 shows that the transient shocks account for no more than 14% of the variations in μ_{jmt} and less than 10% for mc_{jmt} of craft products, and no more than 5% for non-craft products. The out-of-sample performance is similar: with the training sample including as little as 20% of the data, the out-of-sample R^2 becomes comparable to the in-sample ones. The reasonably good fit provides us with further justification to use this specification to construct the mean utility and marginal costs in X_{nm}.

C Details on the Fixed Cost Estimation and Inference

In this section, we explain the estimation procedure step-by-step, including how we estimate the conditional choice probability $\Pr\left(A_{jm} = 1 \mid X_{jm}, X_{-jm}\right)$ and carry out the inference of the fixed cost parameters. We estimate the confidence set in two ways, based on Chernozhukov et al. (2007) (CHT) and Andrews and Shi (2013) (AS).

Figure B.1: In- and Out-of-Sample Fit for μ_{jmt} and mc_{jmt}

(a) In-sample R^2 (b) Out-of-sample R^2



Common steps:

1 For each potential product/market combination jm, we calculate the corresponding extrema $\underline{\Delta}_j(X_m)$ and $\overline{\Delta}_j(X_m)$.

2 We estimate $\Pr(A_{jm} = 1 \mid X_{jm}, X_{-jm})$. Recall that we use X_{jm} to represent both the variable profit covariates X_{jm} and the fixed cost covariates W_{jm}. Therefore, the condition variable vector (X_{jm}, X_{-jm}) is a potentially high-dimensional vector. Similar to the conditional choice probability approach for estimating dynamic models (e.g., Hotz and Miller (1993); Bajari et al. (2007); Ryan (2012)), we assume that it is sufficient to condition on a few summary statistics. Specifically, we consider $\left(\overline{\Delta}_j(X_m), \underline{\Delta}_j(X_m), W_{jm}\right)$. Some of these variables are continuous and the rest are binary. We use Z^c_{jm} to denote the continuous subvector and Z^b_{jm} the binary subvector. Following the construction of instruments in Andrews and Shi (2013), we standardize Z^c_{jm} and transform the vector so that each element lies in $[0, 1]$. Specifically, the transformed vector is $\tilde{Z}^c_{jm} = \Phi\left(\mathit{\Gamma} \cdot Z^c_{jm}\right)$, where $\mathit{\Gamma}$ is the Cholesky decomposition of $Var^{-1}\left(Z^c_{jm}\right)$ and $\Phi(\cdot)$ is the standard normal distribution applied to each element of the vector. We estimate $\Pr(A_{jm} = 1 \mid X_{jm}, X_{-jm})$ by the average of A_{jm} across the 20 observations closest to $\left(\tilde{Z}^c_{jm}, Z^b_{jm}\right)$ measured by Euclidean distance.

For inference following CHT, we define a sample objective function $Q(\theta)$ as

$$Q(\theta) = \frac{1}{\#jm} \sum_{k=1}^{K} \left[\left\| \sum_{m=1}^{M} \sum_{n=1}^{N} \sum_{j \in \mathcal{J}_n} h(X_{jm}, X_{-jm}, \theta) F^{(k)}\left(X_{jm}, X_{-jm}\right) \right\|_{+}^{2} \right], \tag{12}$$

where $\#jm$ indicates the number of observations, where an observation is a combination of a potential product of a firm and a market and $F^{(k)}(X_{jm}, X_{-jm}), k = 1, ..., K$ are non-negative exogenous functions that are constructed as follows: we consider the same transformed vectors

$\tilde{Z}^c_{jm}$ and Z^b_{jm} as in Step 2 above. We then divide the set $(0,1)^{\left|\tilde{Z}^c_{jm}\right|} \times \{0,1\}^{\left|Z^b_{jm}\right|}$ (where $\left|\tilde{Z}^c_{jm}\right|$ and $\left|Z^b_{jm}\right|$ denote the dimensions of $\tilde{Z}^c_{jm}$ and Z^b_{jm}) into $(2r)^{\left|\tilde{Z}^c_{jm}\right|} \cdot 2^{\left|Z^b_{jm}\right|}$ hypercubes, where each interval $(0,1)$ is divided into $\left(0, \frac{1}{2r}\right), \left[\frac{1}{2r}, \frac{2}{2r}\right), \ldots \left[\frac{2r-1}{2r}, 1\right)$. We denote the set of hypercubes by $\{\mathcal{C}_1, ..., \mathcal{C}_K\}$ and construct $F^{(k)}(X_{jm}, X_{-jm})$ as indicator functions $1\left(\left(\tilde{Z}^c_m, Z^b_m\right) \in \mathcal{C}\right)$ for each hypercube $\mathcal{C}_k$. For inference, we use subsampling to take into account the noise introduced in estimating the conditional choice probability in Step 2.

4(CHT) We construct 200 subsamples and each subsample consists of 20% of the data. For each subsample, we re-estimate the conditional choice probabilities in Step 2 and re-compute the objective function in Step 3 at $\left(\hat{\theta}, \hat{\sigma}_\zeta\right)$. We obtain an initial estimate of critical value c_1 as the 95% quantile of $Q^r\left(\hat{\theta}, \hat{\sigma}_\zeta\right)$, where Q^r is the objective function on the rth sample.[17]

5(CHT) We construct a set Θ of 10000 candidate parameters by adding shocks to $\hat{\theta}$ and then define $\Theta_1 = \{\theta \in \Theta : Q(\theta) < c_1\}$.

6(CHT) For each $\theta \in \Theta_1$,we obtain a critical value $c_1(\theta)$ as the 95% quantile of $Q^r(\theta)$ across $r = 1, \ldots, 200$. Define $c_2 = \max_{\theta \in \Theta_1} c_1(\theta)$. We construct the confidence set as $\{\theta \in \Theta : Q(\theta) < c_2\}$.

For inference following AS, we now use $F^{(k),r}(X_{jm}, X_{-jm})$ to denote the non-negative exogenous functions defined above, where r is the integer that controls the fineness of the grid. We use $K(r)$ to denote the number of functions given r.

3(AS) For a candidate vector of parameters θ, define the test statistic T in Andrews and Shi (2013):

$$T(\theta) = \sum_{r=1}^{3} \frac{(2r)^{-d_x}}{(r^2+100)} \cdot \sum_{k=1}^{K(r)} \left\| \frac{\sqrt{\#jm}}{\varpi_{kr}} \frac{1}{\#jm} \sum_{m=1}^{M} \sum_{n=1}^{N} \sum_{j \in \mathcal{J}_n} h(X_{jm}, X_{-jm}, \theta) F^{(k),r}(X_{jm}, X_{-jm}) \right\|_+^2 .$$

We choose the conditioning weights $\frac{(2r)^{-d_x}}{(r^2+100)}$, where d_x is the dimension of conditioned observables, and other tuning parameters (see step 4(AS)) following AS. The weight ϖ_{kr} is standard deviation of the term

$$m_{kr} = \frac{1}{\#jm} \sum_{m=1}^{M} \sum_{n=1}^{N} \sum_{j \in \mathcal{J}_n} h(X_{jm}, X_{-jm}, \theta) F^{(k),r}(X_{jm}, X_{jm}).$$

[17] In practice, to deal with over-identification, we use $Q^r(\theta) - \min_b Q^r(b)$ as the objective function (Chernozhukov et al. (2007)).

This Cramér–von Mises test statistic is a weighted sum of the objective function in (12), with each objective function using a finer definition of the box instruments.

4(AS) We generate bootstrap samples and compute the "re-centered" statistic on each sample

$$T^{\star}(\theta, \sigma_{\zeta}) = \sum_{r=1}^{3} \left\{ \frac{(2r)^{-d_x}}{(r^2+100)} \cdot \sum_{k=1}^{K(r)} \left\| \frac{\sqrt{\#jm}}{\varpi_{kr}^{\star}} (m_{kr}^{\star} - m_{kr}) + \frac{\varpi_{kr}}{\varpi_{kr}^{\star}} \varphi_{kr} \right\|_{+}^{2} \right\}$$

where the superscript $\star$ indicates the quantities calculated on the bootstrapped samples. The shifts of moments φ_{kr} is defined in AS. The idea is to reduce the effects of the moments that are not binding at θ but have large variances.

5(AS) We take the 95% critical value $c_{95}(\theta)$ to be the 95% quantile of the bootstrapped statistic. The 95% confidence set is $\{\theta \in \Theta : T(\theta) < c_{95}(\theta)\}$.

D Fixed Cost Simulation Draws Conditional on Observed Equilibrium Outcomes

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

1. For each potential product j, we calculate an upper and a lower bound of the fixed cost shock ζ_{jm} as follows. If j is in the market before the merger,

$$\tilde{L}_{jm} = -\infty, \tilde{H}_{jm} = \underline{\Delta}_j(X_m)$$

and if product j is not in the market,

$$\tilde{L}_{jm} = \underline{\Delta}_j(X_m), \tilde{H}_{jm} = \infty.$$

2. We simulate draws of the fixed cost shocks from a truncated normal distribution with the underlying normal distribution parameterized by mean 0 and variance $\hat{\sigma}_{\zeta}^2$ and the truncation being $\tilde{L}_{jm} < \zeta_{jm} < \tilde{H}_{jm}$. These draws satisfy the necessary conditions for the observed equilibrium.

3. We next verify these draws indeed support the equilibrium. To do so, we employ the algorithm in Appendix E with the starting points $\mathcal{J}_{nm}^0 = \emptyset$ and $\mathcal{J}_{nm}^0 = \mathcal{J}_n$ and check whether the algorithm converges to $\mathcal{J}_{nm}$, holding $\mathcal{J}_{-nm}$ fixed. If the algorithm converges to $\mathcal{J}_{nm}$ from both starting points, we keep the set of draws for n. If at least one of the starting points does not lead to $\mathcal{J}_{nm}$, we go back to Step 2 and re-draw the fixed costs.

4. We repeat this process for every firm n.

E Equilibrium Computation Details

We conduct the counterfactual simulations using the algorithm in Fan and Yang (2020). At a high level, for each market, we solve for the equilibrium using best response iterations where firms take turns to choose their products until no firm has an incentive to deviate. We use two orderings of firms (i.e., ascending and descending order based on the observed annual sales) and find the same equilibrium. Embedded in the best-response iteration procedure is an optimization problem to determine a firm's best response. Similar to Fan and Yang (2020), firms in our model often face too large a choice set. For example, the merging firms in our counterfactual analysis has a total of 51 potential products, leading to a choice set of $2^{51} \approx 10^{15}$. We thus use a heuristic algorithm described below to determine each firm's best response. Additional discussions and Monte Carlo simulations demonstrating the performance of the algorithm can be found in Fan and Yang (2020).

In the following, we use firm n and market m as an example. Starting with a product portfolio $\mathcal{J}_{nm}^0 \subseteq \mathcal{J}_n$, we compute firm n's profit from each of the following deviations from $\mathcal{J}_{nm}^0$: $\mathcal{J}_{nm}^0 \backslash k$ for $k \in \mathcal{J}_{nm}^0$ or $\mathcal{J}_{nm}^0 \cup k$ for $k \in \mathcal{J}_n \backslash \mathcal{J}_{nm}^0$. Each deviation differs from $\mathcal{J}_{nm}^0$ in only one product: either a product in $\mathcal{J}_{nm}^0$ is removed or a potential product not in $\mathcal{J}_{nm}^0$ is added. There are $\#\mathcal{J}_n$ such deviations. Let $\mathcal{J}_{nm}^1$ be the highest-profit deviating product portfolio. If firm n's profit corresponding to $\mathcal{J}_{nm}^1$ is smaller than that corresponding to $\mathcal{J}_{nm}^0$, this procedure stops and returns $\mathcal{J}_{nm}^0$ as the best response. Otherwise, we compute n's profit from any one-product deviation from $\mathcal{J}_{nm}^1$ by either adding a potential product to or dropping a product from $\mathcal{J}_{nm}^1$. We continue this process until firm n's profit no longer increases. This algorithm allows us to translate a problem whose action space grows exponentially in the number of potential products (choosing from $2^{\#\mathcal{J}_n}$ product portfolios) into one whose action space grows linearly (in each step, evaluating $\#\mathcal{J}_n$ portfolios).

Due to the computational burden, we simulate 35 sets of draws of fixed costs and use them to conduct counterfactuals.

F Monte Carlo Simulations

In this appendix, we use Monte Carlo simulations to examine the performance of our estimation procedure for estimating the fixed cost parameters. Our purposes are two-fold: first, we show that our approximations of $\overline{\Delta}_j$ and $\underline{\Delta}_j$ work well; second, we show that our estimation method generally result in conservative but still reasonably tight confidence set of the true parameters.

We first describe the data generating process. The demand is given by a nested Logit model with a nest over all inside products $\mathcal{J}_m$ in market m. The market share of good j in market m is given by

$$s_{jm}=\frac{\exp\left(\delta_{jm}/\left(1-\rho\right)\right)}{\sum_{j'\in\mathcal{J}_m}\exp\left(\delta_{j'm}/\left(1-\rho\right)\right)}\frac{\exp\left(\left(1-\rho\right)\sum_{j'\in\mathcal{J}_m}\exp\left(\delta_{j'm}/\left(1-\rho\right)\right)\right)}{1+\exp\left(\left(1-\rho\right)\sum_{j'\in\mathcal{J}_m}\exp\left(\delta_{j'm}/\left(1-\rho\right)\right)\right)},$$

where ρ is the nesting parameter and the mean utility is $\delta_{jm}=\alpha p_{jm}+\beta x_{jm}$. We define O_m to be the market size, and the demand for j in market m is $O_m\cdot s_{jm}$. The marginal cost is mc_{jm}. The fixed cost is

$$\theta_0+\theta_1 W_{jm}+\zeta_{jm},$$

where ζ_{jm} follows a normally distribution with mean 0 and variance σ_ζ^2.

We set $\alpha=-0.5$, $\rho=0.2$ and draw x_{jm} and mc_{jm} from a normal distribution with a mean of 2 and a standard deviation of 0.25, truncated on the support of $[1.5,2.5]$. In the fixed cost function, $W_{jm}\sim N\left(0,3\right)$. The market size O_m is uniformly drawn from $(0,O)$. There are two firms per market and they have the same number of potential products. We consider 7 specifications (7 different values for $(O,\beta,\sigma_\zeta,\mu_\zeta,\theta)$ and the number of potential products per firm), and for each specification, we simulate 1000 markets. For each market, we find the equilibrium by enumerating and checking all possible outcomes. When there are multiple equilibria, we assign equal probability to each equilibrium and randomly choose one.

With the simulated data, we conduct two exercises. First, we examine how close our approximations are to the true extrema of the incremental profits. To this end, we compute the true minimum and maximum of the change in variable profit $\underline{\Delta}_{jm}=\min_{a_{-jm}}\Delta_{jm}\left(a_{-jm}\right)$ and $\bar{\Delta}_{jm}=\max_{a_{-jm}}\Delta_{jm}\left(a_{-jm}\right)$ as well as our approximations of them, i.e., $\Delta_{jm}\left(1,...,1\right)$ and $\Delta_{jm}\left(0,...,0\right)$. We find that they match perfectly for all product-market combinations in all specifications.

Second, we estimate the fixed cost parameters $(\theta_0,\theta_1,\sigma_\zeta)$ and obtain the 95% confidence set following the estimation and inference procedure in Appendix C. We report the coverage probability that the confidence set covers the true parameter from simulating the competition between 2 firms in 1000 markets for 7 specifications.

We report the results in Table F.1. We vary our parameter values to adjust the tightness of our bounds, which we measure by the median of the ratio $\frac{\underline{\Delta}_{jm}}{\bar{\Delta}_{jm}}$. A smaller value (meaning the upper bounds are larger than the lower bounds) indicates looser bounds. As explained in Section (2), the tightness of the bounds has a direct impact on estimation. For example, a single agent discrete choice problem, where the ratio is 1, is identified under weaker conditions than discrete games. In our simulated data, the ratio varies between fairly loose (0.18) and fairly tight (0.63). To put the number in perspective, the median ratio is 0.65 in the estimation sample in Section 5.2. We also report the percentage of markets with multiple equilibria in the column "Multi Equi %". The frequency of multiple equilibria overall amounts to a small fraction of the simulated markets (2.50% in the most extreme cases). Finally, because the identified set does not have an analytic form, and simulating it involves solving both the price and product choice equilibria and is computationally costly, we therefore report the coverage probability for the true parameter instead of the identified

Table F.1: Monte Carlo Simulations: 2 firms

	O	β	σ_ζ	μ_ζ	θ	# products/firm	$\text{med}\left(\frac{\underline{\Delta}_{jm}}{\overline{\Delta}_{jm}}\right)$	Multi Equi %	Cvg Rate
(1)	50000	-5	1.5	1.5	1.5	2	0.6	0.03%	98.00%
(2)	100	0	12	3	1.5	2	0.5	1.25%	100.00%
(3)	50	0.8	15	6	1.5	2	0.3	2.50%	100.00%
(4)	50000	-5	1.5	2.5	0.5	2	0.6	0.03%	98.00%
(5)	50000	-5	1.5	0.5	2.5	2	0.6	0.02%	99.00%
(6)	50	0.8	15	15	1.5	2	0.3	1.40%	100.00%
(7)	50	0.8	15	15	1.5	3	0.2	1.27%	100.00%

set in the last column. The coverage is higher than 95%, which is expected, and indeed decreases in $\text{med}\left(\frac{\underline{\Delta}_{jm}}{\overline{\Delta}_{jm}}\right)$.

We next examine the false coverage probabilities of the projected 95% confidence intervals. Typically authors report the false coverage probability defined as the probability that a confidence set includes a point just outside the identified set (for example, Andrews and Shi (2013)). As explained above, the identified set of the model in our Monte Carlo exercise does not have an analytic form, and so it is not possible to precisely pin down the boundary of the identified set. To still give a sense of how "wide" confidence set tends to be, we instead calculate the probabilities that points around the true parameter values are covered by the 95% confidence interval. In Figure F.1, we plot the coverage probabilities by the projected confidence intervals from the confidence sets for points in intervals around the true parameters. We do so for the specifications in Row (1) of Table F.1, where the tightness of the bounds is similar to the empirical setting, and Row (7) of Table F.1, where the bounds are wider. The y-axis of Figure F.1 shows how often a point is included in the confidence interval. When the bounds are tight ($\text{med}\left(\frac{\underline{\Delta}_{jm}}{\overline{\Delta}_{jm}}\right) = 0.63$), the results show the projected confidence intervals are tight: for example, in Figure F.1 (1), the vertical line indicates that the true value of the fixed cost intercept μ is 1.5, and the probability of the confidence interval covering 3.5 or 0.5 is close to 0. When the bounds are more relaxed, the confidence intervals are proportionally wider for $(\sigma_\zeta, \mu_\zeta)$ (relative to the values of the true parameters). The interval is often twice as wide for θ_1. In both cases, the false coverage probabilities of 0 are reasonably small for all parameters across both specifications.

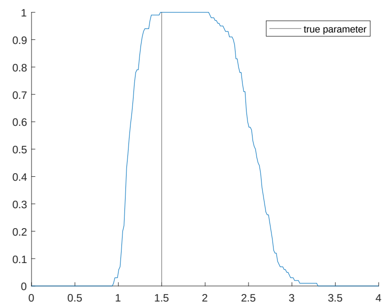
G Market Size-Dependent Fixed Costs

In this section, we present the results where we allow fixed costs to depend on market sizes. Specifically, we define market sizes below the 25% quantile as "small", between 25%–75% as "medium" and above 75% as "large" markets. We modify the baseline fixed cost function to allow for dependence

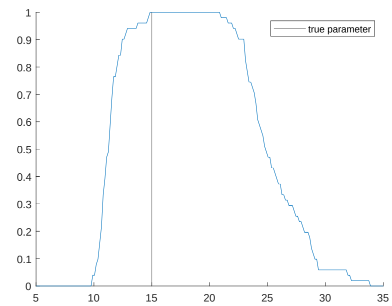
Figure F.1: False Coverage Probability. Left: $\text{med}\left(\frac{\Delta_{jm}}{\overline{\Delta}_{jm}}\right) = 0.63$; Right: $\text{med}\left(\frac{\Delta_{jm}}{\overline{\Delta}_{jm}}\right) = 0.18$

FC Intercept μ

(1) Specification (1)

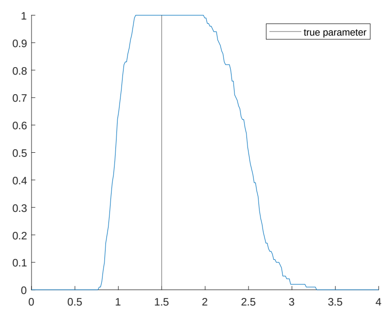


(2) Specification (7)

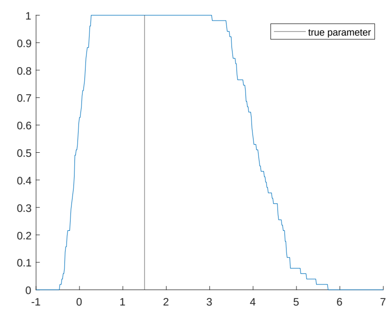


FC Covariate Coefficient θ

(3) Specification (1)

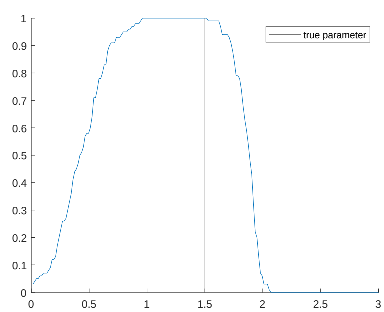


(4) Specification (7)



FC Unobservable Standard Deviation σ_ζ

(5) Specification (1)



(6) Specification (7)

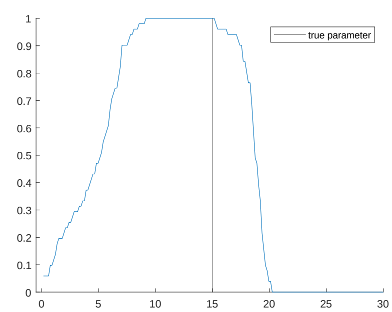


Table G.1: Estimates of Fixed Costs

Craft (θ_1)	[485.88, 2168.68]
In State× Craft (θ_2)	[-656.55, 837.75]
Distance[a] ×In State× Craft (θ_3)	[814.51, 2586.09]
Constant (θ_0^k)	
Small Market	[839.50, 2131.35]
Medium Market	[1400.49, 2384.31]
Large Market	[3655.23, 5815.32]
Std. Dev. (σ_ζ^k)	
Small Market	[90.42, 1218.75]
Medium Market	[471.74, 1305.17]
Large Market	[3465.14, 4917.70]

[a]: Distance in 1000KM

on market sizes:

$$c(W_{jm}, \theta) = \theta_0^k + \theta_1 \text{craft}_j + \theta_2 (\text{in state})_j \cdot \text{craft}_j + \theta_3 (\text{in state})_j \cdot \text{craft}_j \cdot \text{dist}_{jm} + \zeta_{jm}^k,$$

where $k \in \{\text{small}, \text{medium}, \text{large}\}$ and $\zeta_{jm\tau}^k \sim \Phi\left(0, \sigma_\zeta^k\right)$. We use CHT for inference to lessen the computational burden. Table G.1 reports the estimates of the projected 95% confidence sets. Figures G.1 and G.2 report the counterfactual results, which are similar to our baseline.

H (Dis)Economies of Scope

To allow for potential economies or dis–economies of scope in fixed costs, we modify the baseline fixed cost function in Section 4 by adding a parameter θ_4:

$$\theta_4 1\left(\sum_{j \in \mathcal{J}_n} a_{jm} > 0\right) + \sum_{j \in \mathcal{J}_n} a_{jm} \left(c(W_{jm}, \theta) + \zeta_{jm}\right), \tag{13}$$

where

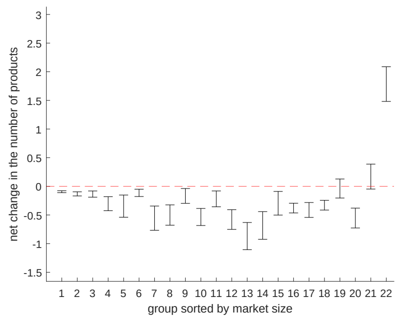
$$c(W_{jm}, \theta) = \theta_0 + \theta_1 \text{craft}_j + \theta_2 (\text{in state})_j \cdot \text{craft}_j + \theta_3 (\text{in state})_j \cdot \text{craft}_j \cdot \text{dist}_{jm}.$$

The fixed cost function in (13) is no longer additive in the fixed cost of each product. If $\theta_4 > 0$ (or < 0), the fixed cost exhibits economies or dis–economies of scope.

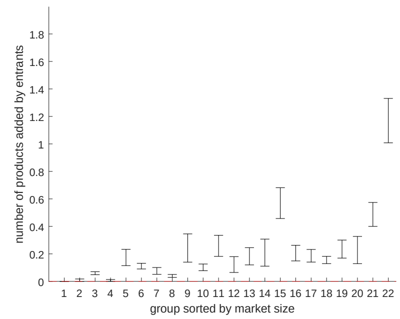
To estimate θ_4, we need to bound the entry probability of a firm in addition to the entry probability of a product. To see why bounding the entry probability of a product is not sufficient, we first modify the bounds in Inequality (11) to take into account the part $\theta_4 1\left(\sum_{j \in \mathcal{J}_n} a_{jm} > 0\right)$.

Figure G.1: Effects of Merger on the Number of Products

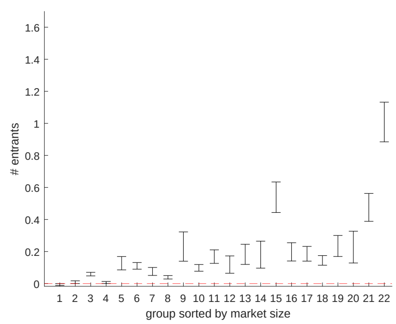
(a) Net Change in the Number of Products



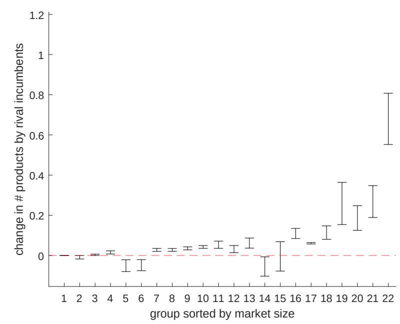
(b) Number of Products Added by Entrants



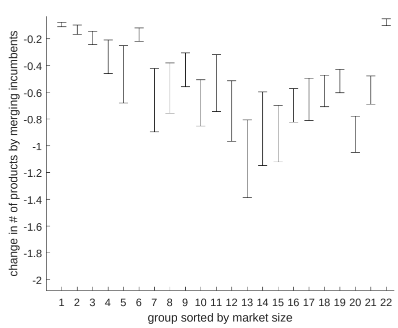
(c) Number of Entrants



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



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



(f) Craft Prices

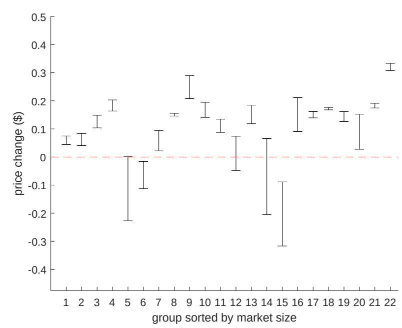
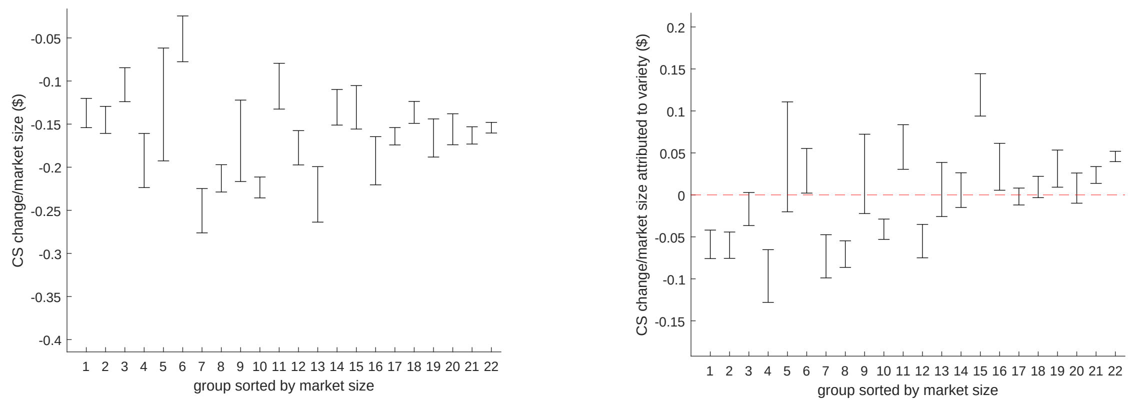


Figure G.2: Average Consumer Surplus

(a) Change in the Average Consumer Surplus

(b) Change in the Average Consumer Surplus Attributed to Variety



The inequality becomes

$$\begin{aligned}
&\Pr\left(\zeta_{jm} < \underline{\Delta}_j(X_m) - c(W_{jm},\theta) - |\theta_4|_+\right) \\
\leq &\Pr\left(A_{jm} = 1 \mid X_{jm}, X_{-jm}, W_{jm}, W_{-jm}\right) \\
\leq &1 - \Pr\left(\zeta_{jm} > \bar{\Delta}_j(X_m) - \mathrm{c}(W_{jm},\theta) + |\theta_4|_-\right),
\end{aligned} \tag{14}$$

where $|\theta_4|_+$ is θ_4 if $\theta_4 > 0$ and 0 otherwise; $|\theta_4|_-$ is $-\theta_4$ if $\theta_4 < 0$ and 0 otherwise. The bounds hold for any value of θ_4: when product j is added, the increased fixed cost is either $c_{jm} + \zeta_{jm} + \theta_4$ or $c_{jm} + \zeta_{jm}$; therefore for the left-hand side, we consider the minimum of the two and for the right-hand side, we consider the maximum of the two. However, the bounds in (14) alone are not sufficient to estimate the fixed cost function, because the bounds become weakly looser when $|\theta_4|$ increases.

To estimate θ_4, we thus additionally consider the following additional inequalities related to the probability that a firm has at least one product in a market: let $a_{nm} = (a_{jm}, j \in \mathcal{J}_n)$ be firm n's product decision in market m and $\#(a_{nm}) = \sum_{j \in \mathcal{J}_n} a_{jm}$ be the number of products firm n sells in market m when its vector of decisions regarding its potential products is a_{nm}. Then

$$\begin{aligned}
&\Pr\left(\sum_{j\in\mathcal{J}_n} A_{jm} > 0 \,|\, X_{jm}, X_{-jm}, W_{jm}, W_{-jm}\right) \\
=&\Pr\left(\max_{a_{nm}\ \text{s.t.}\ \#(a_{nm})>0}\left[\Pi_{nm}\left(a_{nm}, a_{-nm}, X_m\right) - \sum_{j\in\mathcal{J}_n} a_{jm}\left(c(W_{jm},\theta) + \zeta_{jm}\right)\right]\right. \\
&\left. -\theta_4 \,|\, X_{jm}, X_{-jm}, W_{jm}, W_{-jm}\right) > 0.
\end{aligned} \tag{15}$$

By the definition of $\overline{\Delta}_j(X_m)$, we have

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

This gives us the upper bound for the probability in (15)

$$\Pr\left(\max_{a_{nm} \text{ s.t. } \#(a_{nm})>0} \left\{\sum_{j \in \mathcal{J}_n} a_{jm}\left(\overline{\Delta}_j(X_m) - c(W_{jm}, \theta) - \zeta_{jm}\right)\right\} - \theta_4 > 0 \,|\, X_{jm}, X_{-jm}, W_{jm}, W_{-jm}\right) \tag{16}$$

Similarly, we can construct the following lower bound:

$$\Pr\left(\max_{a_{nm} \text{ s.t. } \#(a_{nm})>0} \left\{\sum_{j \in \mathcal{J}_n} a_{jm}\left(\underline{\Delta}_j(X_m) - c(W_{jm}, \theta) - \zeta_{jm}\right)\right\} - \theta_4 > 0 \,|\, X_{jm}, X_{-jm}, W_{jm}, W_{-jm}\right) \tag{17}$$

We can similarly derive bounds for "firm entry with at least two products":

$$\Pr\left(\max_{a_{nm} \text{ s.t. } \#(a_{nm})>1} \left\{\Pi_{nm}\left(a_{nm}, a_{-nm}, X_m\right) - \sum_{j \in \mathcal{J}_n} a_{jm}\left(c(W_{jm}, \theta) + \zeta_{jm}\right)\right\} - \theta_4 > 0 \,|\, X_{jm}, X_{-jm}, W_{jm}, W_{-jm}\right).$$

The bounds above give us additional moments. These bounds do not have analytical forms.We simulate them as follows. We take NS draws of ζ_{jm}'s and index the l^{th} draw for jm combination by $\zeta_{jm}^{(l)}$. The simulation for (16) is

$$\frac{1}{NS}\sum_{l=1}^{NS} 1\left(\sum_{j \in \mathcal{J}_n} \left\|\overline{\Delta}_j(X_m) - c(W_{jm}, \theta) - \zeta_{jm}^{(l)}\right\|_+ - \theta_4 > 0\right).$$

The probability in (17) is simulated analogously. Therefore, the computation is still fast.

Since the bounds are for firm-level entry probabilities, we construct the exogenous non-negative functions $F^{(k)}$ in Appendix C using firm-level variables. Specifically, we first group firms by the number of potential products. Within each group, we use a kmeans algorithm to classify firms by the vector $\left(\tilde{Z}_{jm}^c\right)_{j \in \mathcal{J}_n}$ into r classes, which are transformed continuous product characteristics. We use $\|\mathcal{J}_n\|$ to denote firm n's number of potential products, and $\phi(n) \in \{1, \ldots, r\}$ to denote the kmeans class of firm n. Define

$$\tilde{\boldsymbol{\mathcal{C}}} = \left\{1, \ldots, \bar{J}\right\} \times \{1, \ldots, r\} \times \{0, 1\}^{\left|Z_{jm}^b\right|},$$

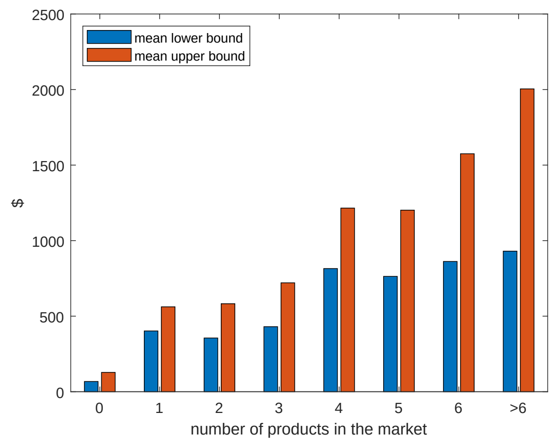
where $\bar{J}$ is the highest number of products per firm. We denote an element of $\tilde{\boldsymbol{\mathcal{C}}}$ as $\tilde{\mathcal{C}}_k$ and construct indicator functions $F^{(k)}$ by whether $\left(\|\mathcal{J}_n\|, \phi(n), Z_{jm}^b\right) = \tilde{\mathcal{C}}_k$.

Table H.1 reports the estimation results. We use CHT for inference to reduce the computational burden. We find dis–economies of scope: the projected CI of the θ_4 is $[-2237.18, -628.20]$. To see what data pattern leads to this estimate, we compute the average $\overline{\Delta}_j(X_m)$ and $\underline{\Delta}_j(X_m)$ across all jm pairs such that the number of products that firm n has in market m is h. We plot these

Table H.1: Estimates of Fixed Costs: 2016

Constant (θ_0)	[2163.79, 3598.07]
Craft (θ_1)	[1866.87, 3357.79]
In State× Craft (θ_2)	[-1288.92, 669.20]
Distance^a×In State× Craft (θ_3)	[-154.33, 2904.70]
Scope (θ_4)	[-2237.18, -628.20]
Std. Dev. (σ_ς)	[862.97, 2329.04]
[a]: Distance in 1000KM	

Figure H.1: Average $\underline{\Delta}_j\left(X_m\right)$ and $\overline{\Delta}_j\left(X_m\right)$, Conditional on the Number of Products by a Firm in a Market

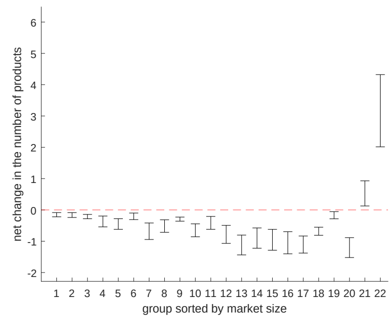


averages for $h = 0, 1, ..., 6$ and > 6 in Figure H.1. The figure suggests that for firms that place more products in a market, the average incremental variable profit are higher. This pattern is suggestive evidence of dis–economies of scope: everything else equal, if the average fixed cost increases in the number of products, in equilibrium we should see that the average variable profit is positively correlated with the number of products by a firm.

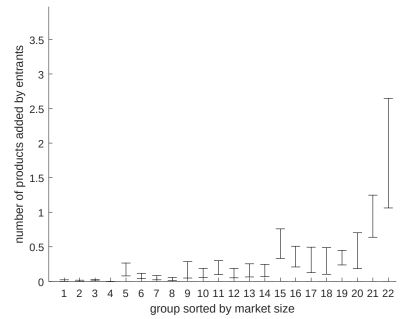
To see the robustness of our results, we repeat the counterfactual simulations in Section (7) using this fixed cost specification and the corresponding confidence set of the parameters. In the merger simulation, we assume that the common owner of the acquired craft breweries coordinates pricing and product entry decisions, but does not change the underlying distribution of fixed costs. Therefore the fixed cost reduction from θ_4 applies to each acquired brewery that enters a market. We report results in Figures H.2 and H.3, corresponding with Figures 4 and 5 and 5. The results are similar.

Figure H.2: Product Variety, Entry and Prices

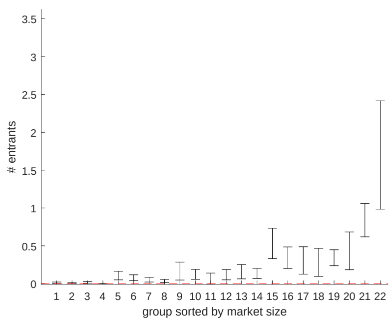
(a) Net Change in the Number of Products



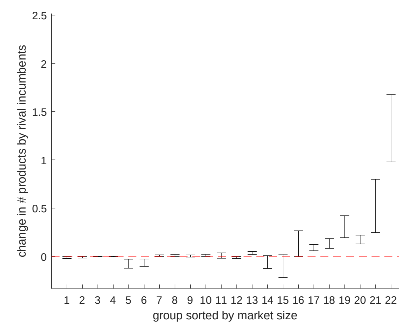
(b) Number of Products Added by Entrants



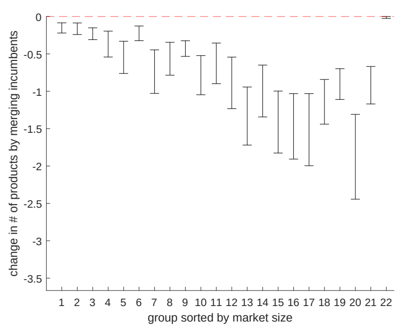
(c) Number of Entrants



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



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



(f) Craft Prices

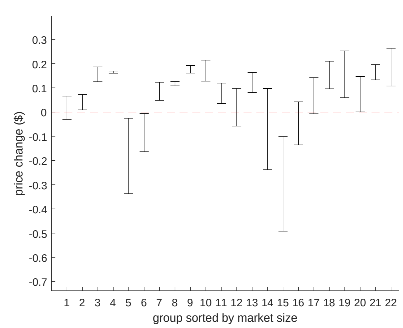
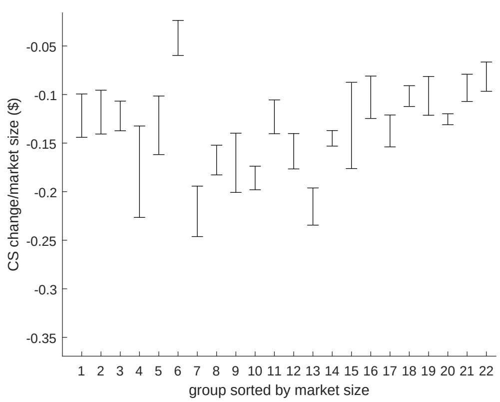


Figure H.3: Average Consumer Surplus

(a) Change in the Average Consumer Surplus



(b) Change in the Average Consumer Surplus Attributed to Variety