Identifying Scale and Scope Economies using Demand-Side Data*

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Abstract

We propose an empirically tractable method to estimate economies of scale and scope. We start from a micro-founded model of production by a multi-product firm and generate a set of estimating equations for the parameters governing scale and scope economies, together with the distribution of within-firm productivity. A strength of the method is that all parameters can be estimated using demand-side data only (i.e., quantities, prices, demand shifters). We apply this approach to the U.S. beer industry to quantify the importance of scope economies for productive efficiency and evaluate the impact of scale and scope economies on merger analysis.

Keywords: Economies of scope, boundaries of the firm, productivity, multiproduct firms

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1 Introduction

Multiproduct firms have come to dominate industrial production (Bernard et al., 2010; Goldberg et al., 2010). Economies of scope—cost savings that arise due to the scope of production—have been proposed as one explanation for the existence of multiproduct firms and for production to be consolidated (Panzar and Willig, 1975; Teece, 1980; Panzar and Willig, 1981). Are economies of scope and scale empirically relevant for a firm's decision to expand its horizontal boundaries? Does producing more varieties and consolidating production in fewer plants lead to significant cost savings?

Quantifying economies of scale and scope also has practical relevance for antitrust practitioners. Investigating the competitive impact of a merger between multiproduct firms will generally require assessing a set of (in)efficiencies that go beyond the Williamson tradeoff (Williamson, 1968). For example, the price effects of a merger may lead to a decrease in the scale of production of the merging firms, potentially increasing marginal costs of production due to a loss in scale economies. As well, the merging firms' plants may increase the varieties produced if they produce the products of their merging partners, potentially creating scope economies. Do omitting these scale and scope effects substantially change the conclusions of merger evaluations?

Tackling these and other applied questions requires a methodology to estimate scale and scope economies. To this end, we propose a new method to estimate scale and scope economies suitable for applied work. We start by setting up a multiproduct cost function at the plant level. The technology allows for (but does not impose) economies of scale and scope at the plant level, meaning that it can be more cost-effective to manufacture multiple products within the same plant rather than producing them in separate plants. Following Baumol et al. (1982), we show that this cost function can be derived from a production technology relying on non-rival inputs, e.g., managerial tasks, or machinery that can be used to produce many products simultaneously, which give rise to scope economies. The model allows for multiple plants per firm, multiple cities, and transportation costs that make it costly for a firm to ship goods from a plant to a city.

Our methodology has two key strengths. First, we show that we can identify and estimate all the parameters of the multiproduct cost function using demand-side data only (i.e., quantities, prices, demand shifters). No data on inputs, input allocation across products, or input prices is needed. This makes our method relatively easy to implement for industry studies where researchers have access to the data needed to estimate a demand system. Second, multiproduct cost functions can suffer from a dimensionality problem, as the function must specify how an increase in the quantity of product j impacts the marginal cost of product k. This may create a practical problem for the econometrician—in particular, when the set of products is large—since estimation requires one instrument per parameter in the model. We tackle this issue using a parsimonious micro-founded model where two parameters govern scale and scope economies.

Using the marginal cost function for each product, we derive two equations that are linear in the key technology parameters governing scale and scope economies, which makes estimation appear straightforward. However, estimation requires us to resolve two econometric challenges. First, econometricians rarely observe marginal costs in their data. We propose overcoming this issue by estimating the marginal cost for each product using the demand-side approach, pioneered in Rosse (1970), and further developed by Berry et al. (1995), Nevo (2000), and Berry and Haile (2014). The two key elements of this approach are demand system estimates and a product market game specification. Using the system of first-order conditions for profit maximization evaluated at the observed prices, we can recover point estimates of the marginal costs. We can use these marginal costs and the observed output levels together with our marginal cost model to estimate the production parameters of interest.

The second challenge we face is that estimating production parameters using a standard ordinary least squares (OLS) methodology will likely introduce bias due to endogeneity issues. These issues are associated with firms making decisions about the output level for each product while considering the unobserved productivity of the corresponding product line. To tackle this concern, we note that the output levels are determined by the interaction of supply-side and demand-side forces through firms' pricing first-order conditions. We, therefore, propose using demand-side taste shocks as instruments, which can be computed based on demand model estimates. As noted, the parsimony of the model also restricts the number of instruments needed, which is a practical strength of our method.

Having solved these two challenges, we identify the magnitude of scale and scope economies by comparing the production technology's returns to scale (i.e., the sum of the output elasticities of all inputs) with the sum of the output elasticity of rival inputs. If the returns to scale are greater than the output elasticity of rival inputs, then this suggests the existence of non-rival inputs and, hence, scope economies. We identify returns to scale by examining how costs change with exogenous increases in output. Although we do not directly observe rival inputs, we expand on techniques developed in Orr (2022) to identify the share of rival inputs allocated towards a particular production line. Combining this result with exogenous variation in product-line specific output shares, allows us to identify the output elasticity of rival inputs.

We then use our methodology to investigate the existence of scope economies in the US beer industry. This industry is ideal for two reasons. First, the main players are multiproduct firms (e.g., Anheuser-Busch, Molson Coors, SABMiller, Grupo Modelo, among other active firms in our sample period). Second, firms in the industry produce using a small number of plants despite high transportation costs. For example, Molson Coors had two plants (Colorado and Virginia) serving the entire United States up until 2008. This contrasts with other industries where local production is preferred to save on transportation costs (e.g., the US carbonated beverage industry). These facts combined are consistent with scale and scope economies at the brewery level.

Our main data source is the IRI Marketing Dataset (Bronnenberg et al., 2008), which provides price and sales data at the store–week–product level, where a product is defined as a brand–size combination (e.g., Budwesier, 6-pack). We focus on the years 2005 to 2008. Given that our study periods overlap, we make use of the demand system estimates in Miller and Weinberg (2017).

Our estimates for the US beer industry suggest the existence of both scale economies and scope economies. We use these estimates to address several economic questions of interest. In the first counterfactual analysis, we measure the impact of scope economies on productive efficiency and market outcomes. We shut down scope economies (keeping all other aspects of the production technology fixed, including scale economies) and compute equilibrium market outcomes.

How do scope economies impact pricing and production decisions? On the one hand, the increase in the marginal cost of a product caused by the shutdown of scope economies decreases the marginal incentive to sell an extra unit of that good, incentivizing a price increase. On the other hand, our estimates suggest the existence of economies of scale, making it costly to cut down production, as this would further inflate marginal costs. Economies of scale make price increases costly, creating a tradeoff.

The comparison of equilibria suggests that shutting down scope economies increases marginal costs by 33.9 percent on average relative to the equilibrium with scope economies. The effect on marginal costs is magnified by a decrease in output (market shares decrease on average by 2.2 percent). That is, scope economies are stronger than scale economies for production decisions because firms choose to cut production despite scale economies. We also find that prices increase by 19.8 percent on average in the equilibrium without scope economies. These findings combined suggest that scope economies have a first-order effect on productive efficiency—providing an (at least partial) explanation for why multiproduct production is favored in this industry—and market outcomes.

We then explore the role of scope and scale economies in merger analysis. We simulate the impact of the joint venture between CoorsMolson and SABMiller, which took place in

2008. One efficiency that was cited is that CoorsMolson and SABMiller would be able to leverage the breweries of the other firm, which would on average decrease the distance that the products of both firms would need to travel to reach consumers. Our model captures this efficiency gain but also captures an inefficiency that is a direct consequence of this: as production becomes more fragmented (i.e., less output per brewery), firms miss out on scale and/or scope economies. This inefficiency may lessen or overwhelm the shipping cost savings of producing closer to consumers.

A comparison of the equilibria with and without the joint venture shows that the marginal costs of MillerCoors decreased by 6.5 percent on average. This combined effect is a result of multiple factors: cost decreases due to (i) scope economies as brewing facilities expand their range of products, (ii) transportation cost savings, and (iii) production being reallocated to more efficient breweries. However, these decreases are strongly attenuated by the decrease in brewery-level scale, with many breweries shipping to fewer markets and pulling back production in order to enable price raises. Eventually, these cost increases and the enhanced market power of the merged company result in an increase in prices of 2.2% percent (although the estimate is noisy) and a 1.8% decrease in the market share of MillerCoors products, on average. These average effects, however, mask significant heterogeneity across products and markets. Overall, these findings highlight that scale and scope economies are relevant for analyzing mergers, especially where production occurs across multiple plants.

The rest of the paper is organized as follows. Section 2 presents the literature review. The model is discussed in Section 3, and we present our identification and estimation strategy in Section 4. Section 5 describes our empirical application, which is the U.S. beer industry. Section 6 concludes.

2 Literature Review

We contribute to several strands in the literature. First, we contribute to the literature on testing for the existence of non-joint production and scope economies. Previous approaches have either relied on cost function estimation using firm-level cost data (Hall 1973, Kohli 1981, Baumol et al. 1982, Johnes 1997, Zhang and Malikov 2022) or estimation of multi-output technologies using transformation functions (Dhyne et al. 2022, Maican and Orth 2020). These approaches require high-quality data on inputs and costs, which in practice is difficult to find for many industries, and may be prone to measurement error.[1] Our paper, on the other hand, provides a way to test for and quantify non-joint production by relying only on *demand-side* data, i.e. prices, quantities, and market shares. Importantly, we do

[1]See, for example, the recent discussion in De Loecker and Syverson (2021).

not require that a researcher have access to any input or cost data. Instead, our approach builds on the demand-side approach to cost estimation, pioneered in Rosse (1970), and further developed by Berry et al. (1995), Nevo (2000), and Berry and Haile (2014), where a firm's pricing first order conditions are used to back out point estimates of marginal cost. We consider a simple parameterization of a firm's cost function that allows for joint and non-joint production and show how to generate simple estimating equations for parameters governing scale and scope economies.[2]

In this sense, our paper is closely related to Ding (2022) and Argente et al. (2020), who also provide evidence of scale and scope economies. While we share an interest in many of the same questions, we differ from these papers in a number of important ways. To estimate and quantify scale and scope economies, Ding (2022) proposes a model of joint production driven by public inputs that generate ideas that can be applied to various industries within a multi-industry conglomerate. Argente et al. (2020) considers an alternative model where a firm can invest in firm-wide or product-specific knowledge. Our model largely differs from these papers by relying on a microfoundation for joint production based on public or non-rival production inputs, as in Baumol et al. (1982), rather than scope economies generated by knowledge or idea generation. We also provide a complementary "micro" study—focused on a single industry, beer—to complement the more aggregate "macro", across-industry, approach employed in these studies.

Second, we contribute to the body of work investigating various productivity and competition issues in the US beer industry (Ashenfelter et al., 2015; De Loecker and Scott, 2016; Miller and Weinberg, 2017; Grieco et al., 2018; Miller et al., 2021). Our key contribution is to investigate the existence of scope economies and study their implication for efficiency and market outcomes, which sets us apart from prior work. Fan and Yang (2022) also investigate the existence of scale and scope economies in the US beer industry. Their work complements ours as they study scale and scope economies based on fixed costs of entering a market (i.e., entry may have a firm and product-specific cost), and they estimate entry costs based on observed entry decisions. Our papers differ in the source of scale and scope economies (returns to scale in variable and non-rival inputs versus fixed costs) and the variation used to estimate scope economies (prices versus entry decisions).

Finally, we contribute to the literature on synergies in mergers and acquisitions. While merger-related synergies represent one of the central concerns in antitrust, empirical studies

[2]The particular form of the cost function we rely on has been used in previous literature (Baumol et al. 1982, Johnes 1997). However, our estimation approach is more flexible than previous approaches, since we explicitly allow for the existence of firm-product-market specific shocks to productivity, which we are able to recover naturally using our marginal cost inversion, relying on insights from Orr (2022) and Cairncross et al. (2023).

in this area are surprisingly limited (Asker and Nocke, 2021). We contribute to a handful of studies investigating merger-related efficiencies (for example, Jeziorski, 2014,Ashenfelter et al., 2015, Grieco et al., 2018, Elliott et al., 2023; see an overview in Asker and Nocke, 2021). While many of these studies are relatively context-specific, our approach has the potential to be applied more broadly. Within this literature, our paper is closest to Grieco et al. (2018). Both studies enable the forecasting of post-merger changes in marginal costs using solely pre-merger data, which is particularly valuable from an antitrust perspective. An important distinction is that while Grieco et al. (2018) focuses on scale economies, our analysis also incorporates the economies of scope. Moreover, while Grieco et al. (2018) relies on input data, our method solely requires demand-side data, which is already commonly used in merger evaluations.

3 A Model of Supply with Scale and Scope

Standard demand estimation approaches to merger analysis (e.g. Hausman et al. 1994, Nevo 2000, among others) often assume that firms face constant marginal costs of production following an ownership change. This requires abstracting from both economies of scale and scope in variable costs, both of which can have important effects on post-merger outcomes. For example, when economies of scale matter, post-merger upward pricing pressure has a further effect on firms' costs; specifically, as price increases decrease the firm's overall scale, costs can rise, which decreases efficiency and may lead to greater price increases. Similarly, if economies of scope matter, where costs of production fall as firms produce many varieties due to input sharing, there may be efficiency gains that counterbalance upward pricing pressure in some mergers.

The key benefit to assuming constant returns to scale is the empirical tractability, as supply-side parameters necessary to simulate merger counterfactuals are exactly identified when demand and each firm's pricing rule are known. For example, for the standard case of Bertrand-Nash price competition, the set of pricing first-order conditions that must be satisfied can be written in matrix form as follows:

$$\mathbf{Q}_{ct} + \Delta_{ct} \left(\mathbf{P}_{ct} - \mathbf{MC}_{ct} \right) = 0, \tag{1}$$

where $(\mathbf{Q}_{ct}, \mathbf{P}_{ct})$ are vectors of quantities and prices charged in each market c at time t, $\mathbf{MC}_{ct}$ is a vector of marginal costs, and Δ_{ct} is the element-by-element product of two matrices; a matrix of cross-price derivatives for the firm's demand system (∂_{ct}) with typical element (k, n) equal to $\frac{\partial Q^k_{ct}}{\partial P^n_{ct}}$, and an ownership matrix ($\mathbb{O}_{ct}$) where element (k, n) equals 1 if product

k and n are produced by the same firm, zero otherwise.

Typically in this setting, the econometrician observes $(\mathbf{Q}_{ct}, \mathbf{P}_{ct})$, using which they can obtain Δ_{ct} using demand estimation techniques. Marginal costs $\mathbf{MC}_{ct}$ are known to the firms but not the econometrician. An estimate of the vector of marginal costs can be obtained by inverting the system of first-order conditions, yielding:

$$\mathbf{MC}_{ct} = \mathbf{P}_{ct} + \Delta_{ct}^{-1}\mathbf{Q}_{ct} \tag{2}$$

Equation (2) provides exactly one marginal cost value for each specific combination of market, time period, firm, and product that rationalizes the firm's pricing decisions under a particular conduct assumption. Under the further restriction of constant marginal cost, knowing this number is sufficient for merger counterfactuals, as marginal costs are invariant to the scale of production, as well as the set of products produced.

However, with scale and scope economies, point identifying marginal costs through (2) is no longer sufficient for counterfactual analysis. Rather, marginal costs will generally be functions of the scale of own production line (due to scale economies), as well as the scale of *other* production lines (due to scope economies). As a result, these marginal cost *functions* need to be identified to conduct counterfactual merger analysis.

We show that it is possible to estimate a marginal cost function with scale and scope economies by adding two extra steps to the standard approach discussed above. For this purpose, we rely on the following CES cost function (Baumol et al. 1982, Johnes 1997), which we define over the set of products j produced at a particular production location b at time t:[3]

$$C_{bt}(\mathbf{Y}_{bt}, \mathbf{A}_{bt}, \mathbf{W}_{bt}) = g(\mathbf{W}_{bt}) \left(\sum_{j \in \mathbb{J}_{bt}} \left(\frac{Y_{bt}^{j}}{A_{bt}^{j}} \right)^{\frac{1}{\alpha}} \right)^{\frac{\alpha}{\phi}} \tag{3}$$

where $\mathbb{J}_{bt}$ denotes the set of products produced in location b at time t, $\mathbf{W}_{bt}$ is a vector of input prices faced in location b at time t, $\mathbf{Y}_{bt} = \{Y_{bt}^{j}\}_{j \in \mathbb{J}_{bt}}$, is the vector of outputs j produced, $\mathbf{A}_{bt} = \{A_{bt}^{j}\}_{j \in \mathbb{J}_{bt}}$ is a vector of product-specific productivity shifters, and $g(.)$ is a homogenous of degree one function. This functional form specification offers several advantages. First, it allows for scale and scope economies in a tractable manner.[4] Second, it is micro-founded

[3] b stands for brewery, as in our empirical application below. However, our model can be applied in many other settings.

[4] One straightforward alternative would be a flexible polynomial function that includes interaction terms for outputs from different product lines. However, this approach has its drawbacks, including a significant practical limitation: as the product count grows, it becomes increasingly susceptible to the curse of dimensionality.

(see Appendix B), allowing for a clear interpretation of the parameters outlined below.

The technology parameters ϕ and α govern the magnitude of scale and scope economies. We show this formally in Appendix B, where we provide a derivation of this cost function based on the primal representation of a firm's technology using product-line specific production functions that allow for *non-rival inputs* in production; e.g. managerial inputs or machinery that can be used to produce many products simultaneously. This derivation allows us to provide a clear interpretation of the parameters α and ϕ. In particular, ϕ is equal to the returns to scale of the product-level production function, while $\beta_p \equiv \phi - \alpha$ captures the intensity of public, non-rival tasks in production. If $\beta_p \equiv \phi - \alpha = 0$, then the technology simplifies to the standard case of non-joint production, where there are no cost inter-dependencies across products.

Importantly, this technology generates economies of scope— i.e. it is cheaper to produce multiple outputs in the same location than in multiple locations with the same underlying productivity parameters — whenever $\beta_p = \phi - \alpha > 0$. We show this formally through the following Lemma.

Lemma 1 *For a given vector of outputs $\mathbf{Y}_{bt} > 0$, let $\mathbf{Y}^j_{bt}$ denote a corresponding vector of outputs where all elements are zero except for the j'th element which equals $Y^j_{bt} > 0$ from $\mathbf{Y}_{bt}$. Then,*

- $C(\mathbf{Y}_{bt}, \mathbf{A}_{bt}, \mathbf{W}_{bt}) < \sum_{j \in \mathbb{J}_{bt}} C(\mathbf{Y}^j_{bt}, \mathbf{A}_{bt}, \mathbf{W}_{bt})$ *if* $\phi > \alpha$.
- $C(\mathbf{Y}_{bt}, \mathbf{A}_{bt}, \mathbf{W}_{bt}) = \sum_{j \in \mathbb{J}_{bt}} C(\mathbf{Y}^j_{bt}, \mathbf{A}_{bt}, \mathbf{W}_{bt})$ *if* $\phi = \alpha$;
- $C(\mathbf{Y}_{bt}, \mathbf{A}_{bt}, \mathbf{W}_{bt}) > \sum_{j \in \mathbb{J}_{bt}} C(\mathbf{Y}^j_{bt}, \mathbf{A}_{bt}, \mathbf{W}_{bt})$ *if* $\phi < \alpha$.

Proof. See Appendix A □

Note that the cost function $C(\mathbf{Y}^j_{bt}, \mathbf{A}_{bt}, \mathbf{W}_{bt})$ corresponds to the cost function for a single-product firm producing Y^j_{bt}. Lemma 1 shows that when $\phi > \alpha$, $C(\mathbf{Y}_{bt}, \mathbf{A}_{bt}, \mathbf{W}_{bt})$ will be strictly smaller than the cost of producing the vector $\mathbf{Y}_{bt}$ through J separate production processes. As a result, economies of scope mean that production costs are lower when firms produce multiple products together, potentially providing a rationale for firms to consolidate the production of many products in a single location. On the other hand, when $\phi = \alpha$, the firm essentially operates J separate production processes, and as a result, there are no cost savings to producing multiple goods together. Finally, the case $\phi < \alpha$ involves *diseconomies of scope*, where production costs rise when a firm produces many outputs.[5]

[5] We do not expect this case to arise empirically since, in these situations, a firm would choose to operate the J independent product lines, which would generate lower costs.

The model also allows for transportation cost, which is one of the margins of adjustments that can be relevant for counterfactual analysis if firms reallocate their products across locations. In order to take the transportation costs into account, we distinguish between total quantities produced at a location b, Y^j_{bt} and the total quantities shipped and sold to a particular market c (e.g. a city), which we will denote by Q^j_{ct}. To allow for distribution costs associated with shipping goods from the production location b to final consumers in city c, we assume that shipping across locations is constrained by product-specific iceberg trade costs, where $\tau^j_{bct} \geq 1$ units of a good must be shipped to market (c, t) for each unit of the good to arrive.[6] More formally, if a firm wishes to sell outputs $\{Q^j_{ct}\}_c$ across each city c, then total output at the production location b, Y^j_{bt} must satisfy:

$$Y^j_{bt} = \sum_c Q^j_{ct}\tau^j_{bct} = Q^j_{ct}\exp(\lambda Z^j_{bct} + \widetilde{\tau}^j_{bct}) \tag{4}$$

where Z^j_{bct} is a vector of observables that affect transportation costs (e.g. distance from the city), and $\widetilde{\tau}^j_{b(i)ct}$ are transportation costs that are unobservable to the econometrician.

Combining (4) with (3) yields the following cost function defined over the outputs chosen by firm i for sale in each city c, $\mathbf{Q}_{bt}$:

$$C_{bt}(\mathbf{Q}_{bt}, \mathbf{A}_{bt}, \mathbf{W}_{bt}) = g(\mathbf{W}_{bt}) \left(\sum_{j \in \mathbb{J}_{bt}} \left(\sum_{c \in \mathbb{C}^j_{bt}} \frac{Q^j_{ct}}{\Omega^j_{bct}} \right)^{\frac{1}{\alpha}} \right)^{\frac{\alpha}{\phi}} \tag{5}$$

where $\Omega^j_{bct} \equiv \frac{A^j_{bt}}{\tau^j_{bct}}$ is transportation-cost adjusted productivity in market c for product j, and $\mathbb{C}^j_{bt}$ denotes the set of cities where production location b ships product j.

Note that the potential existence of scale in equation (5) generates cross-market interactions in costs. In particular, if there are scale economies at the product level, so $\phi > 0$, then equation (5) implies that costs will fall in the city c if the output is scaled up in markets $c' \neq c$. This also generates potential efficiency gains by consolidating production in a single location.

Given this cost function, the pricing game we assume for each firm is standard, i.e. static Nash-Bertrand pricing. Specifically, each firm i chooses the price of each product j in each

[6]This modelling assumption generates cost functions that are multiplicative in transportation costs — as is assumed in Miller and Weinberg (2017), for example — and is standard in quantitative spatial models; see Costinot and Rodríguez-Clare (2014) or Redding (2022).

city c to maximize its profits, given the prices of its rivals:

$$\max_{\{P_{cit}^{j}\}_{(j,c)\in(\bigcup_{c\in\mathbb{C}}\mathbb{J}_{ict})}} \sum_{c\in\mathbb{C}}\sum_{j\in\mathbb{J}_{ct}} P_{ct}^{j} Q_{ct}^{j}(\mathbf{P}_{ct}) - \sum_{b\in\mathbb{B}_i} C_{bt}\left(\mathbf{Q}_{bt}(\mathbf{P}_t), \mathbf{A}_{bt}, \mathbf{W}_{bt}\right), \tag{6}$$

where $\mathbb{J}_{ict}$ denotes the set of products j produced by firm i that are sold in city c, and $\mathbf{Q}_{bt}(\mathbf{P}_t)$ denotes the vector of demands for all products and cities served by brewery b, which depends on the equilibrium price vector. In the equilibrium, each element $Q_{ct}^{j}(\mathbf{P}_{ct})$ of the vector is equal to the quantity supplied for each product and market.

The equilibrium vector of prices $\mathbf{P}_t$, solves the system of first-order conditions,

$$Q_{ct}^{j} + \sum_{k\in\mathbb{J}_{ict}} \left(P_{ct}^{k} - \underbrace{\frac{\partial C_{b(k,c)t}\left(\mathbf{Q}_{bt}(\mathbf{P}_t), \mathbf{A}_{bt}, \mathbf{W}_{bt}\right)}{\partial Q_{ct}^{k}}}_{\equiv MC_{it}^{j}(\mathbf{Q}_{bt}(\mathbf{P}_t),\mathbf{A}_{bt},\mathbf{W}_{bt})} \right) \frac{\partial Q_{ct}^{k}(\mathbf{P}_{ct})}{\partial P_{ct}^{j}} = 0, \quad \forall j \in \mathbb{J}_{cit}, \forall i, \forall c \tag{7}$$

where $b(k,c)$ denotes the location where product k sold in market c is produced, and given (5), marginal cost functions are given by:

$$MC_{ct}^{j}\left(\mathbf{Q}_{bt}(\mathbf{P}_t), \mathbf{A}_{bt}, \mathbf{W}_{bt}\right) = \frac{1}{\phi} g(\mathbf{W}_{bt}) \left(\sum_{j\in\mathbb{J}_{bt}} \left(\sum_{c\in\mathbb{C}_{bt}^{j}} \frac{Q_{ct}^{j}}{\Omega_{bct}^{j}} \right)^{\frac{1}{\alpha}} \right)^{\frac{\alpha}{\phi}-1} \left(\sum_{c\in\mathbb{C}_{bt}^{j}} \frac{Q_{ct}^{j}}{\Omega_{bct}^{j}} \right)^{\frac{1}{\alpha}-1} \frac{1}{\Omega_{bct}^{j}} \tag{8}$$

Equations (7) and (8) nest the standard case considered in many empirical merger papers of Bertrand-Nash pricing with constant marginal costs when $\alpha = \phi = 1$, in which case $MC_{ct}^{j} = \frac{g(\mathbf{W}_{bt})}{A_{bt}^{j}}$. Note, however, that even if there are nonconstant marginal costs as in (8), equations (1) and (2) continue to hold at the equilibrium values of each firm-product's marginal cost.[7] We shall use this property of the model to help identify the marginal cost function in the following section.

4 Estimation of Scale and Scope Economies

Having specified the pricing game and each firm's cost function, we now turn to the estimation of the marginal cost function specified in (8). For this purpose, it will be useful be rewrite that function as follows:

[7] While this model generates across market interactions through the marginal cost function, these do not show up in Δ_{ct} since $\frac{\partial Q_{ct}^{k}(\mathbf{P}_{ct})}{\partial P_{c't}^{j}} = 0$ for $c' \neq c$.

$$MC_{ct}^{j}=\underbrace{\frac{g(\mathbf{W}_{bt})}{\phi\Omega_{bt}^{\frac{1}{\phi}}}}_{\equiv K_{bt}}\left(\sum_{j\in\mathbb{J}_{bt}}\left(\sum_{c\in\mathbb{C}_{bt}^{j}}\frac{Q_{ct}^{j}}{\widehat{\Omega}_{bct}^{j}}\right)^{\frac{1}{\alpha}}\right)^{\frac{\alpha}{\phi}-1}\left(\sum_{c\in\mathbb{C}_{bt}^{j}}\frac{Q_{ct}^{j}}{\widehat{\Omega}_{bct}^{j}}\right)^{\frac{1}{\alpha}-1}\frac{1}{\widehat{\Omega}_{bct}^{j}} \tag{9}$$

where we substitute $\Omega_{bct}^{j}=\Omega_{bt}\widehat{\Omega}_{bct}^{j}$, where $\ln\Omega_{bt}\equiv\frac{1}{\sum_{j\in\mathbb{J}_{bt}}|\mathbb{C}_{bt}^{j}|}\sum_{j\in\mathbb{J}_{bt}}\sum_{c\in\mathbb{C}_{bt}^{j}}\ln\Omega_{bct}^{j}$ and $\ln\widehat{\Omega}_{bct}^{j}\equiv\ln\Omega_{bct}^{j}-\ln\Omega_{bt}$. Finally, $K_{bt}\equiv g(\mathbf{W}_{bt})/\phi\Omega_{bt}^{\frac{1}{\phi}}$ shifts the marginal costs of all products equally. It is possible to fully recover the marginal cost function for the purpose of running counterfactuals by estimating $(\alpha,\phi,\{\widehat{\Omega}_{bct}^{j}\}_{(j,b,c,t)})$, as well as the components of $\{K_{bt}\}_{(b,t)}$. Notice that since $\widehat{\Omega}_{bct}^{j}=\frac{A_{bt}^{j}}{\Omega_{bt}\tau_{bct}^{j}}=\frac{A_{bt}^{j}}{\Omega_{bt}\exp(\lambda Z_{bct}^{j}+\widetilde{\tau}_{bct}^{j})}$, additionally estimating $\left(\lambda,\{\frac{A_{bt}^{j}}{\Omega_{bt}}\}_{(j,b,t)},\{\widetilde{\tau}_{bct}^{j}\}_{(j,b,c,t)}\right)$ allows to study how marginal cost, as well as equilibrium prices and quantities change with distance.

Note that equation (2) allows us to recover an estimate of the *equilibrium value* of each product's marginal cost $MC_{ct}^{j}\equiv\frac{\partial C_{b(j,c)t}(\mathbf{Q}_{bt})}{\partial Q_{ct}^{j}}$. The following subsection describes a step-by-step procedure that uses these values together with the equilibrium (observed) quantities Q_{ct}^{j} within the equation (9) in order to estimate all the parameters described above.

Step 1.

To generate an estimating equation for $(\alpha,\{\widehat{\Omega}_{bct}^{j}\}_{(j,b,c,t)})$, first multiply equation (9) by Q_{ct}^{j}, and divide this expression by its sum over all $c\in\mathbb{C}_{bt}^{j}$:

$$\frac{MC_{ct}^{j}Q_{ct}^{j}}{\sum_{c\in\mathbb{C}_{bt}^{j}}MC_{ct}^{j}Q_{ct}^{j}}=\frac{\frac{Q_{ct}^{j}}{\widehat{\Omega}_{bct}^{j}}}{\sum_{c\in\mathbb{C}_{bt}^{j}}\frac{Q_{ct}^{j}}{\widehat{\Omega}_{bct}^{j}}} \tag{10}$$

Second, use the sum over $c\in\mathbb{C}_{bt}^{j}$, and divide it by the sum over both $c\in\mathbb{C}_{bt}^{j}$ and $j\in\mathbb{J}_{bt}$, yielding:

$$\frac{\sum_{c\in\mathbb{C}_{bt}^{j}}MC_{ct}^{j}Q_{ct}^{j}}{\sum_{j\in\mathbb{J}_{bt}}\sum_{c\in\mathbb{C}_{bt}^{j}}MC_{ct}^{j}Q_{ct}^{j}}=\frac{\left(\sum_{c\in\mathbb{C}_{bt}^{j}}\frac{Q_{ct}^{j}}{\widehat{\Omega}_{bct}^{j}}\right)^{\frac{1}{\alpha}}}{\sum_{j\in\mathbb{J}_{bt}}\left(\sum_{c\in\mathbb{C}_{bt}^{j}}\frac{Q_{ct}^{j}}{\widehat{\Omega}_{bct}^{j}}\right)^{\frac{1}{\alpha}}}=\left(\frac{\sum_{c\in\mathbb{C}_{bt}^{j}}\frac{Q_{ct}^{j}}{\widehat{\Omega}_{bct}^{j}}}{Q_{bt}}\right)^{\frac{1}{\alpha}} \tag{11}$$

where

$$Q_{bt} = \left(\sum_{j \in \mathbb{J}_{bt}} \left(\sum_{c \in \mathbb{C}^j_{bt}} \frac{Q^j_{ct}}{\widehat{\Omega}^j_{bct}} \right)^{\frac{1}{\alpha}} \right)^{\alpha} \tag{12}$$

is a location-level output aggregator. As shall be clear in a moment, the first stage estimating equation will allow us to estimate this object, which will then be a key ingredient for our second stage estimating equation.

Using equation (10) to rewrite the numerator in (11) and then rearranging, we can generate the following estimating equation:

$$\ln Q^j_{ct} = \alpha \ln S^j_{bt} + \ln S^{c|j}_{bt} + \ln Q_{bt} + \ln \widehat{\Omega}^j_{bct} \tag{13}$$

where $S^j_{bt} \equiv \frac{\sum_{c \in \mathbb{C}^j_{bt}} MC^j_{ct} Q^j_{ct}}{\sum_{j \in \mathbb{J}_{bt}} \sum_{c \in \mathbb{C}^j_{bt}} MC^j_{ct} Q^j_{ct}}$ and $S^{c|j}_{bt} = \frac{MC^j_{ct} Q^j_{ct}}{\sum_{c \in \mathbb{C}^j_{bt}} MC^j_{ct} Q^j_{ct}}$. Appendix B shows that within the model of public and private tasks, α represents the output elasticity of private or rival inputs, while in Appendix C, we show that S^j_{bt} represents the share of rival inputs allocated towards product j; a novel extension to the identification result in Orr (2022) to a setting with non-joint production.

From this expression, we can see that α is identified from the variation in this share while keeping constant the total location-level output Q_{bt}. In other words, α is identified by reallocating rival inputs towards product j and evaluating how much the output of product j scales up as a result. Note that in practice, since Q_{bt} is not known as it depends on α, we can still estimate the parameter using linear regression by differencing Q_{bt} out and relying on the within-location variation.

Identification of α requires exogenous variation in S^j_{bt}. However, both components of S^j_{bt}, specifically Q^j_{ct} and MC^j_{ct}, directly depend on $\widehat{\Omega}^j_{bct}$, which suggests the need for instruments. To find appropriate instruments, note that Q^j_{ct} is determined by the interaction of both supply side and *demand-side* forces through a firm's pricing first-order conditions (7). In other words, a positive shock in demand would lead to the firm reallocating rival inputs towards product j, thus increasing S^j_{bt}. This suggests relying on product-city-specific demand shocks as a way to shift S^j_{bt} within a firm and thereby identify α.

Having recovered $\ln \widehat{\Omega}^j_{bct}$ from equation (13), parameters $\left(\lambda, \{ \frac{A^j_{bt}}{\Omega_{bt}} \}_{(j,b,t)}, \{ \widetilde{\tau}^j_{bct} \}_{(j,b,c,t)} \right)$ can be identified from the following equation:

$$\ln \widehat{\Omega}^j_{bct} = -\lambda Z^j_{bct} + \ln \left(\frac{A^j_{bt}}{\Omega_{bt}} \right) - \widetilde{\tau}^j_{bct}, \tag{14}$$

which can be estimated using OLS with fixed effects. Note that λ is identified from co-variation between observables Z_{bct}^{j} (for example, distance from the production location to the destination city) and location-product-city level productivity while keeping location-product level productivity constant.

Step 2.

In order to create an equation that allows to estimate $(\phi, \{K_{bt}\}_{(b,t)})$, notice that we can use equation (9) to write $\ln\left(\sum_{j\in\mathbb{J}_{bt}}\sum_{c\in\mathbb{C}_{bt}^{j}} MC_{ct}^{j}Q_{ct}^{j}\right)$ in the following way:

$$\ln\left(\sum_{j\in\mathbb{J}_{bt}}\sum_{c\in\mathbb{C}_{bt}^{j}} MC_{ct}^{j}Q_{ct}^{j}\right) = \frac{1}{\phi}\ln Q_{bt} + \ln K_{bt}, \tag{15}$$

where $K_{bt} \equiv \frac{g(\mathbf{W}_{bt})}{\phi\Omega_{bt}^{\frac{1}{\phi}}}$ and Q_{bt} is the location-level output aggregator defined above.

Notice that once α is recovered in step 1, Q_{bt} is known. Then, ϕ is identified from co-variation in the total location-level output and location-level cost. Analogous to a single product case, if there are increasing returns to scale an increase in total output will be associated with a less-than-proportional increase in costs, while under constant or decreasing returns the same output increase will generate an equal or more-than-proportional cost increase. If the resulting ϕ is larger than α, that would imply that the location-level cost increases slower with output than what we would expect based on the elasticity of private inputs alone. This "wedge" is explained by the presence of public tasks in production, implying economies of scope.

Identification of ϕ again requires instruments, since Q_{bt} depends on K_{bt}. Similar to the strategy for identifying α, it is possible to rely on demand shocks. However, in this case, an ideal instrument needs to shift the overall output of a particular location. In order to create such an instrument, we suggest aggregating demand shocks across all products and cities served by location b.

5 Empirical Application: the MillerCoors Merger

Our empirical application focuses on the well-known joint venture between SABMiller and Molson Coors within the U.S. brewing industry, approved in June of 2008. This setting is well-suited for our analysis, as large brewing companies are typically multiproduct firms, producing a diverse range of beer brands. Moreover, despite these firms operating multiple brewing sites, the number of such locations is relatively limited. Ascher (2012) reports that the U.S. brewing industry, initially characterized by thousands of local breweries, saw a dramatic decline to approximately 22 traditional breweries by 2002. This trend suggests a significant increase in returns to scale and scope at the brewery level. Multiple sources agree that the technological shift in the 1960s and 1970s induced these changes (Kerkvliet et al., 1998; Ascher, 2012; Keithahn, 1978).[8] The technological advancements include improvements in the bottling/canning and packaging technology; the automation of brewing processes, enabling large-scale operations with minimal labor; and innovations in the fermentation process (see Keithahn (1978), p. 34-39 for more detail).[9]

The joint venture between Miller and Coors was approved despite increasing concentration in an already concentrated industry. Prior to the merger, the top five brands accounted for about 80% of sales by 2001, with the merging parties being the second and third largest in the industry (Miller and Weinberg, 2017).[10] The merger received approval primarily due to anticipated synergies in shipping costs, as Coors was going to be able to use Miller's more geographically diverse set of brewing facilities, thereby gaining closer access to various geographical markets (Ashenfelter et al., 2015). Our methodology enables an in-depth analysis of the merger's potential impact on prices and other market outcomes, considering not only changes in concentration and shipping costs but also how economies of scale and scope might be affected due to the reallocation of products across breweries.

5.1 Data

Our main data source is the IRI Marketing Dataset (see Bronnenberg et al., 2008 for a detailed description), which provides price and sales data at the store–week–product level for the years 2001 to 2012. A product is defined as a brand–size combination, and we focus on three sizes: 6-pack equivalent, 12-pack equivalent, and 24/30-pack equivalent. We follow the replication package of Miller and Weinberg (2017) to prepare the data for estimation and restrict attention to January 2005 to May 2008, right before the Miller–Coors joint venture was completed. We focus on this period to abstract away from the price effects of the Miller–Coors joint venture (Miller and Weinberg, 2017; Miller et al., 2021). We refer the reader to Miller and Weinberg (2017) for summary statistics.

We complement these data with the Public Use Microdata Sample (PUMS) of the Amer-

[8] Before that, scale and scope economies were present but moderate, originating mostly from general brewery overhead and utilities. Keithahn (1978, p. 33) suggests that those included "the cost of wells, water-processing equipment, sewage facilities, refrigeration equipment, management, laboratories, and custodial costs".

[9] Notice that some of these technologies might allow for both economies of scale and scope. For example, brewing large quantities of the same type of beer or brewing multiple different types of beers in a large brewery might result in the same labor savings compared to a smaller plant.

[10] Miller and Weinberg (2017) use the following five overarching brand categories: ABI, Miller, Coors, Modelo, and Heineken. These brand categories each aggregate multiple smaller brands. For example, Coors category includes brands such as Coors and Coors Light, among others.

ican Community Survey. We use these data to incorporate demographic variables into the demand system. For every geographic area in the IRI data, we use 500 draws of the distribution of income per person. We use the same draws used by Miller and Weinberg (2017). Lastly, we use data on the location of breweries and allocate each product sold in each geographic market in the IRI dataset to the nearest brewery as in Miller and Weinberg (2017). To estimate transportation costs, we construct a measure of distance based on the interaction of driving miles and diesel fuel prices (see Miller and Weinberg (2017) for details).

5.2 Empirical Model of Demand for Beer

The first step in our approach is estimating demand to derive both own- and cross-price elasticities. These elasticities are then used within equation (2) to estimate marginal costs. Our empirical model of demand for beer uses the random coefficients nested logit model estimated in Miller and Weinberg (2017), which we briefly summarize here. The conditional indirect utility that consumer m receives from purchasing product $j \in \mathbb{J}_{ct}$, where j indexes a particular product in market (c,t) (a particular city c at time t) is given by:[11]

$$u^j_{mct} = \delta^j_{ct} + \mu^j_{mct} + \zeta^{g(j)}_{mct}(\varrho) + (1-\varrho)\epsilon^j_{mct}, \tag{16}$$

where δ^j_{mct} is the mean utility of product j in market (c,t), μ^j_{mct} is the consumer-specific deviation in the valuation of product j from its market-specific mean which depends on product characteristics and consumer demographics, and $\zeta^{g(j)}_{mct}(\varrho)+(1-\varrho)\epsilon^j_{mct}$ is the remaining consumer taste heterogeneity that is distributed extreme value. As in Miller and Weinberg (2017), this structure of the unobserved consumer heterogeneity follows the assumptions of a two-level nested logit model and allows substitution patterns within a group (or a nest) to differ from substitution patterns across groups. The size of this difference is determined by the nesting parameter $0 \leq \varrho < 1$. Since $\zeta^{g(j)}_{mct}(\varrho)$ is common to all products in group g, and ϵ^j_{mct} is i.i.d. extreme value, larger values of ϱ correspond to a stronger correlation in preferences for products within the same group.[12] As in Miller and Weinberg (2017), here we use two groups $g = 0, 1$, where group 0 includes only the outside option $j = 0 \in \Upsilon^0_{ct}$ (e.g. buy no beer) and group 1 includes all the other products $j \in \Upsilon_{ct}$, which we denote by Υ^1_{ct}.

The mean and consumer specific utilities δ^j_{ct} and μ^j_{mct} are parameterized as follows:

$$\delta^j_{ct} = \mathbf{X^j}\beta + \gamma P^j_{ct} + \sigma^j + \sigma_t + \xi^j_{ct} \tag{17}$$

[11] To help the reader keep track of indexes, we always report product-related index as superscripts, while location/time/firm specific indexes are reported as subscripts.

[12] $\zeta^{g(j)}_{mct}(\varrho)$ follows a distribution, which depends on ϱ, that makes $\zeta^{g(j)}_{mct}(\varrho) + (1-\varrho)\epsilon^j_{mict}$ follow an extreme value distribution.

$$\mu_{mct}^{j} = [P_{ct}^{j}, \mathbf{X^j}]\Pi D_m \tag{18}$$

where $\mathbf{X^j}$ denotes observable product characteristics that in our analysis include calories and a constant term, P_{ct}^{j} is the price of product j in market (c,t), σ^j is a product specific intercept, σ_t is a time period t specific intercept, and ξ_{ct}^{j} is the unobserved product quality. (γ, β) then denote the average valuation of price and various product characteristics, respectively. D_m denotes (demeaned) consumer income, and Π is a vector of parameters governing how (γ, β) vary across consumers according to their demeaned income. The outside option payoff is normalized to zero so that $\delta_{ct}^{0} + \mu_{mct}^{0} = 0$.

Given these distributional assumptions, the market share of product j in market (c,t) is given by $s_{ct}^{j}(\mathbf{P}_{ct})$, where $\mathbf{P}_{ct}$ is the vector of prices of all products in market (c,t), can be written as:[13]

$$s_{ct}^{j}(\mathbf{P}_{ct}) = \frac{1}{N_{ct}} \sum_{m=1}^{N_{ct}} \frac{\exp\left(\frac{\delta_{ct}^{j}(P_{ct}^{j}) + \mu_{mct}^{j}(P_{ct}^{j})}{1-\rho}\right)}{\exp\left(\frac{I_{mct}^{g}}{1-\rho}\right)} \frac{\exp\left(I_{mct}^{g}\right)}{\exp\left(I_{mct}\right)} \tag{19}$$

where N_{ct} is the number of consumers in market (c,t), $I_{mct}^{g} = (1-\rho)\sum_{j\in\Omega_{ct}^{g}} \exp\left(\frac{\delta_{ct}^{j}(P_{ct}^{j}) + \mu_{mct}^{j}(P_{ct}^{j})}{1-\rho}\right)$ is the inclusive value for groups $g = 0, 1$ according to consumer m in market (c,t), and $I_{mct} = \log\left(1 + \exp(I_{mct}^{1})\right)$ is the inclusive value for the entire market (c,t). Here, we write $\delta_{ict}^{j}(P_{ict}^{j})$ and $\mu_{mict}^{j}(P_{ict}^{j})$ to emphasize that the consumer-specific payoffs to each good depend are functions of each good's price (through equations 17 and 18).

Since we rely on Miller and Weinberg (2017)'s demand model, we simply take their estimates of (γ, β, Π) as given. Appendix D contains more information about the estimates of the demand parameters we use. Given those estimates, we can construct δ_{ct}^{j} using the information on $s_{ct}^{j}(\mathbf{P}_{ct})$ and the standard Berry (1994) inversion. Then, assuming that firms engage in Bertrand-Nash pricing, we can then recover an estimate of marginal cost by firm-product-market using a standard marginal cost inversion as in equation (2).

5.3 Estimation of the Supply-Side Parameters

Having estimated the marginal costs, we can follow our approach described in Section 4 to estimate the parameters of the cost function. We can rewrite equation (13) in the following way:

[13] Here, we assume the number of consumers is large enough so that we can "integrate out" $\zeta_{mct}^{g(j)}(\varrho) + (1 - \varrho)\epsilon_{mct}^{j}$.

$$\ln \widehat{Q}^j_{ct} - \ln \widehat{S}^{c|j}_{bt} = \alpha \ln \widehat{S}^j_{bt} + \ln \widehat{\Omega}^j_{bct}, \tag{20}$$

where $\ln \widehat{Var} = \ln Var - \frac{1}{\sum_{j \in \mathbb{J}_{bt}} |\mathbb{C}^j_{bt}|} \sum_{j \in \mathbb{J}_{bt}} \sum_{c \in \mathbb{C}^j_{bt}} \ln Var^j_{bct}$. That is, we subtract the brewery-level average from both sides of the equation. Notice that since $\ln Q_{bt}$ does not vary within a brewery, it does not enter the transformed regression equation.

Having recovered the marginal costs, we can construct $\ln \widehat{S}^{c|j}_{bt}$ and $\ln \widehat{S}^j_{bt}$. Notice that now we have the data to estimate α from equation (20) using OLS. However, as discussed earlier, the estimate would likely be biased since $\widehat{S}^j_{bt}$ would generally be correlated with $\widehat{\Omega}^j_{bct}$, the (demeaned) brewery-product-city-specific productivity shock. Notice that the bias may be either positive or negative, depending on the correlation between $\widehat{S}^j_{bt}$, the equilibrium share of rival inputs allocated towards product j in brewery b at time t, and all the characteristics of the production process captured in $\widehat{\Omega}^j_{bct}$. In other words, firms may tend to allocate more rival inputs to more or less productive processes, which would affect the direction of the bias.

Given the endogeneity of $\widehat{\Omega}^j_{bct}$, we use instrumental variables to estimate α. Specifically, we use the demand shocks that affect the equilibrium quantity of product j sold in the city c but are not correlated with the productivity term. As discussed earlier, given the estimated discrete choice demand model, we can recover the mean utility of product j in market (c, t), δ^j_{ct}, and obtain an estimate of the unobserved product appeal ξ^j_{ct} (see equation 17). We will construct our instrument based on ξ^j_{ct}. The first issue that we need to resolve is that ξ^j_{ct} may not be comparable across markets, as, given the way the demand model is estimated, ξ^j_{ct} should, in fact, be interpreted as the difference in the product's appeal for consumers on the market (c, t) relative to that specific market's outside option. As a result, if the outside option differs by market, ξ^j_{ct} may not be properly comparable across markets. To deal with this, we define $\xi^{jR}_{ct} \equiv \xi^j_{ct} - \xi^r_{ct}$ as the difference in the product appeal relative to a reference good r that is offered in all markets, which we take to be 6-packs of Bug Light.[14] Secondly, note that the estimate of ξ^{jR}_{ct} would reflect both the unobserved product quality as well as the market (e.g., city×time) specific taste shocks. Since product quality may be correlated with (quantity) productivity, we include product fixed effects to control for it.

OLS and IV results can be found in columns (1) and (2) of Table 1. After estimating α, equation (20) also allows us to obtain the productivity shocks $\widehat{\Omega}^j_{bct}$, demeaned at the brewery-month level. We can then proceed to estimate the relationship between productivity and transportation cost using equation (14). Specifically, assuming that the productivity term $\ln A^j_{bt}$ is a sum of product and brewery-specific shocks, we estimate:

[14]Notice that since equation (20) uses demeaned variables, we also demean the demand shocks on the brewery level.

Table 1: Parameter Estimates

	(1) OLS	(2) IV	(3) OLS	(4) OLS	(5) OLS	(6) IV	(7) IV
$\widehat{\alpha}$	0.964***	1.128***					
	(0.011)	(0.014)					
$\widehat{\lambda}$			0.0001***				
			(0.000)				
$\frac{1}{\widehat{\phi}}$				0.806***	0.781***	0.802***	0.781***
				(0.014)	(0.015)	(0.017)	(0.029)
First Stage F-stat	-	3,198.76	-	-	-	3,176.48	347.39
$\widehat{\phi}$	-	-	-	1.241	1.280	1.248	1.280
	-	-	-	(0.026)	(0.045)	(0.027)	(0.049)
$\widehat{\phi} - \widehat{\alpha}$	-	-	-	0.112	0.152	0.119	0.151
	-	-	-	(0.024)	(0.046)	(0.024)	(0.048)
Product FE	Yes	Yes	-	-	-	-	-
Brewery-Time FE	-	-	Yes	-	-	-	-
Product-Time FE	-	-	Yes	-	-	-	-
Brewery FE	-	-	-	No	Yes	No	Yes
N	89,910	89,910	89,910	902	902	902	902

Notes: Standard errors, clustered by brewery-month, in parentheses. P-value $< .01 : ***$, P-value$< .05 : **$, P-value$< .1 : *$

$$\ln \widehat{\Omega}^j_{bct} = -\lambda Z^j_{bct} + \ln A^j_t + \ln \left(\frac{A_{bt}}{\Omega_{bt}} \right) - \widetilde{\tau}^j_{bct}, \tag{21}$$

where Z^j_{bct} includes a constant and a geographic distance from brewery b to market c interacted with fuel prices, $\ln A^j_t$ and $\ln \left(\frac{A_{bt}}{\Omega_{bt}} \right)$ are product-month and brewery-month fixed effects, and $\widetilde{\tau}^j_{bct}$ is the error term. The estimate of λ is provided in column (3) of Table 1. Similar to previous work (Miller and Weinberg, 2017; Ashenfelter et al., 2015), our analysis shows a negative and significant relationship between distance and productivity (and therefore the marginal cost): increasing the distance measure by one standard deviation decreases log-productivity $\ln \widehat{\Omega}^j_{bct}$ by 0.15 standard deviations.

Finally, having estimated α and the productivity shocks $\widehat{\Omega}^j_{bct}$, we can construct the measure of Q_{bt} and use equation (15) to estimate ϕ. Again, OLS estimates may be biased since the output aggregator Q_{bt} is likely to be correlated with input prices $\mathbf{W}_{bt}$, as well as the average brewery productivity Ω_{bt}. In order to correct for this bias, we construct instrumental variables relying on brewery-level total taste shocks $\xi^R_{bt} = \ln \left(\sum_{j \in \mathbb{J}_{bt}} \sum_{c \in \mathbb{C}^j_{bt}} \exp(\xi^{jR}_{ct}) \right)$ as our instrument.[15] To additionally control for the fact that there can be a systematic difference

[15]Note that we first exponentiate the taste shocks so that the sum of the demand shocks is in levels, and

between large and small breweries in terms of productivity or input prices, we include the brewery fixed effect.

Columns (4)-(7) of Table 1 report the OLS and IV estimates of $\frac{1}{\phi}$. Both columns use the IV estimate of α from column (2) of the same table to construct the aggregator Q_{bt}.

At the bottom part of the table, we present point estimates and standard errors for $\widehat{\phi}$ and $\widehat{\phi} - \widehat{\alpha}$. As in Grieco et al. (2018), we also find evidence of scale economies, although our estimate (1.280) is slightly larger than their preferred average returns to scale estimates (1.17 - 1.20). To account for uncertainty in the first step of the estimation, the standard errors associated with the estimates of $\widehat{\phi}$ and $\widehat{\phi} - \widehat{\alpha}$ are constructed using block bootstrap, where we sample brewery-time observations with replacement and conduct 100 replications of the two-step procedure for each bootstrap sample. Standard errors are based on the sample standard deviation of the relevant statistic.

Notice that using our estimates and bootstrapped standard errors, we can construct a t-statistic for whether $\widehat{\phi}$ is strictly greater than $\widehat{\alpha}$, and our estimates reject the null of no economies of scope in the beer industry. Finally, equation (15) also allows us to obtain the estimates of K_{bt}. Appendix E discusses how components of K_{bt} necessary for implementing our counterfactuals are estimated.

5.4 The Impact of Scope Economies on Market Outcomes

How do scope economies impact market outcomes in the US beer industry? How relevant are scope economies in explaining firms' marginal costs? We address these questions by comparing the observed equilibrium with a counterfactual equilibrium in which we shut down economies of scope (i.e., no joint production occurs, but the production technology otherwise stays the same). In this counterfactual scenario, $\alpha = \phi$, which, together with equation (9), results in the following marginal cost of producing good j at brewery b for market (c, t):

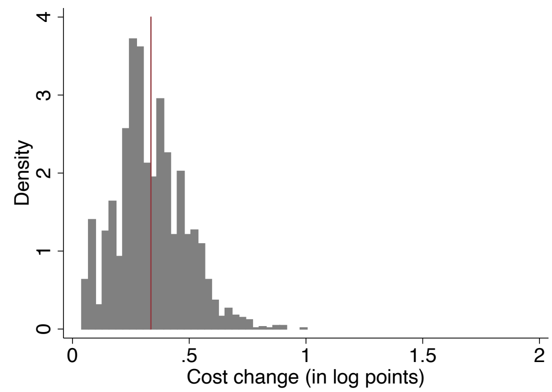
$$MC_{ct}^{\text{non-joint},j}(\mathbf{Q}_{bt}, \mathbf{A}_{bt}, \mathbf{W}_{bt}) = K_{bt} \left(\sum_{c \in \mathbb{C}_{bt}^{j}} \frac{Q_{ct}^{j}}{\widehat{\Omega}_{bct}^{j}} \right)^{\frac{1}{\phi}-1} \frac{1}{\widehat{\Omega}_{bct}^{j}} \tag{22}$$

Lemma 2 in the Appendix shows that the marginal cost of production of a good is lower with joint production when $\phi > \alpha$, which is what our estimates suggest for the US beer industry.

We quantify the impact of joint production on marginal costs in two steps. We first hold quantities produced fixed and compute the counterfactual marginal costs using equation

then take the log of the this total demand shock proxy. We rely on this particular structure as it mimics the structure of our output aggregator that we are instrumenting; see equation (12).

Figure 1: Cost Change when Shutting Down Scope Economies at Observed Quantities



Notes: An observation is a product–city combination. We restrict attention to one time period: January 2005. The histogram displays the distribution of $\log(MC^{\text{no scope economies}}) - \log(MC^{\text{observed}})$, where MC^{observed} is the outcome in the observed equilibrium.

(22). We present the results in Figure 1, which shows cost changes (in log points) for each product–market combination in our data when shutting down scope economies. The figure shows that the marginal cost of production of a product in our sample increases by about 33.6 percent on average (at the observed quantities).

How do these cost increases impact pricing incentives? On the one hand, the increase in the marginal cost of a product decreases the firm's marginal incentives to sell the product, which creates an incentive to increase the price of the good to lower the quantity sold. On the other hand, the existence of increasing returns to scale (i.e., $\hat{\phi} > 1$ in the US beer industry) suggests the existence of a tradeoff: an increase in price decreases quantity, which further increases the marginal cost of production. This makes a price increase costly for the firm.

To quantify how these pricing incentives play out in equilibrium, Table 2 compares the counterfactual equilibrium in which scope economies are shut down with the observed equilibrium. In the counterfactual equilibrium, firms fully adjust prices and production. To compute the counterfactual prices, we replace the marginal cost of production of good j with $MC_{ibt}^{\text{non-joint},j}$ (see equation (22)), and we solve the system of first-order conditions of the pricing game in equation (7). Note that the marginal cost function is nonlinear in the vector of quantities $\mathbf{Q}_{bt}$, implying that the solution to the system of first-order conditions will depend on $\{\mathbf{Q}_{bt}\}_b$. At equilibrium, the prices that solve the first-order conditions at the vector of quantities $\{\mathbf{Q}_{bt}\}_b$ must be such that consumer demand at those prices imply quantities $\{\mathbf{Q}_{bt}\}_b$. Because of the computational burden of solving for the market equilibrium, we consider all product–city combinations but we focus on one time period (May 2008).

Table 2 shows that shutting down scope economies causes prices to increase by 19.8

Table 2: The Impact of Scope Economies on Market Outcomes

	(1)	(2)	(3)	(4)	(5)	(6)
	Price change (in log points)		Cost change (in log points)		Share change (in log points)	
Overall	0.198		0.339		-0.022	
	(0.002)		(0.003)		(0.003)	
Anheuser-Busch		0.201		0.403		-0.017
		(0.003)		(0.004)		(0.004)
FEMSA		0.095		0.120		-0.012
		(0.009)		(0.009)		(0.005)
Grupo Modelo		0.172		0.237		-0.004
		(0.008)		(0.005)		(0.012)
Coors Molson		0.211		0.291		-0.015
		(0.006)		(0.007)		(0.007)
Pabst		0.276		0.426		-0.060
		(0.018)		(0.015)		(0.010)
SABMiller		0.194		0.285		-0.052
		(0.005)		(0.006)		(0.004)
Observations	2,317	2,317	2,317	2,317	2,317	2,317

Notes: Standard errors in parentheses. An observation is a product–city combination. We restrict attention to one time period: May 2008. Each column displays regression coefficients of $\log(X^{\text{counterfactual}}) - \log(X^{\text{observed}})$ on a constant (row Overall of each panel) or firm-level indicators (all other rows), for $X \in \{\text{price}, \text{marginal cost}, \text{market share}\}$, and where X^{observed} is the outcome in the observed equilibrium. "Initial Quantities" indicates that the quantities in the observed equilibrium are used for computing the marginal costs; "Equilibrium Quantities" indicates that the quantities in the counterfactual equilibrium are used for computing the marginal costs.

percent on average. The effects are heterogeneous across firms—the larger price increases are among the firms with the largest number of products (Anheuser-Busch, Coors Molson, and SABMiller), which have the most to lose when shutting down scope economies. Pabst also increases its prices significantly, as Pabst beer is brewed by SAB Miller, exposing it to the loss of scope economies. Market shares on average decrease by 2.2 percent, which makes production even less efficient, as firms miss out on scale economies. Shutting down scope economies (including the interaction with scale economies) causes an increase in the marginal cost of production of 33.9 percent on average—that is, the price increases magnify the scope-induced cost increases because firms take less advantage of scale economies. As with prices, Anheuser-Busch, Molson Coors, Pabst, and SABMiller are the firms with the largest effects on their market shares and marginal costs of production.

Our estimates of economies of scope suggest that these have a first-order effect on market outcomes. The results also show that scale and scope economies reinforce each other—when both are present, they interact, making it cheaper for firms to sell each additional unit. Our findings also show that scope economies and joint production have an economically significant impact on productive efficiency, providing an (at least partial) explanation for the existence of multiproduct firms in the US beer industry.

Table 3: The Impact of the Coors-Miller Joint Venture on Market Outcomes

	(1)	(2)		(3)	(4)		(5)	(6)
	log(price)			log(marginal cost)			log(market share)	
	Merged	Non-merged		Merged	Non-merged		Merged	Non-merged
Scope	-0.203	-0.195		-0.288	-0.362		0.033	0.017
	(0.007)	(0.010)		(0.003)	(0.003)		(0.009)	(0.008)
Merger	0.160	0.009		0.186	0.003		-0.020	0.007
	(0.016)	(0.007)		(0.014)	(0.001)		(0.009)	(0.002)
Merger × Distance savings	-0.036	0.005		-0.070	-0.002		-0.007	-0.000
	(0.007)	(0.004)		(0.009)	(0.000)		(0.005)	(0.001)
Merger × New FEs	-0.059	0.007		-0.106	0.004		0.005	-0.004
	(0.019)	(0.004)		(0.024)	(0.001)		(0.008)	(0.001)
Merger × Scope	-0.043	-0.009		-0.074	-0.003		0.004	0.001
	(0.008)	(0.008)		(0.002)	(0.001)		(0.006)	(0.002)
Observations	7260	15910	.	7260	15910	.	7260	15910
R^2	0.817	0.871	.	0.838	0.938	.	0.658	0.668
Sum of merger coefficients	0.022	0.013		-0.065	0.003		-0.018	0.004
	(0.025)	(0.005)		(0.036)	(0.001)		(0.010)	(0.002)

Note: Standard errors clustered at the market level in parentheses. An observation is a product–city pair for a particular combination of the indicators merger, scope, distance savings, new FEs. We restrict attention to one time period: May 2008. Merged firms correspond to SABMiller and Coors Molson. Non-merged firms correspond to all other firms. The last two rows report the sum of all the merger coefficients as well as its standard error (in parentheses).

5.5 Scope and Scale Economies in Merger Analysis

A potential efficiency gain of the Coors-Miller joint venture was that Coors and Miller products would have to travel shorter distances to reach consumers, as each merging firm could leverage the network of breweries of the other merging firm (Ashenfelter et al., 2015). However, when scale and scope economies are present, there is a tradeoff between consolidating production and saving on shipping costs. That is, fragmenting production over a larger number of breweries may lessen a different type of efficiency caused by consolidating production: scope and scale economies. The Coors-Miller joint venture thus creates tension between these two forces: scope and scale economies versus shipping cost savings.

How did the joint venture impact market outcomes? What is the role of scope and scale economies in explaining these results? To address these questions, we evaluate the effect of the merger on costs, prices, and market shares. We then proceed to disaggregate this effect into components associated with distinct features of the estimated supply model. Firstly, we consider the effect of reallocating production to geographically closer breweries, which may lead to transportation cost savings. Secondly, we take into account the impact of brewing operations being reallocated to more or less productive locations (e.g., locations with higher or lower $\widetilde{K}_{bt} \equiv g(\mathbf{W}_{bt})/(\phi A_{bt}^{\frac{1}{\phi}})$, which reflects variation in productivity and input prices across breweries and comprises the major component of K_{bt}). Thirdly, we assess the influence of scope economies, taking into account that some locations may start brewing larger quantities of a larger variety of products while others may lose products. Lastly, we evaluate the effects stemming from the changing scale of production associated with its fragmentation due to breweries serving fewer markets after the merger.

In order to disaggregate the effect of the joint venture, we compare the observed pre-merger market outcomes with a variety of scenarios. Specifically, we run the following counterfactual experiments: pre-merger environment absent scope economies, as well as post-merger environment with and without (i) scope economies, (ii) changes in distances, and (iii) changes in brewery-level productivities (fixed effects). In counterfactual scenarios without scope economies, we use equation (22) to calculate marginal costs. In experiments concerning distances, we assume either that products get assigned new (shorter) distances or that they have to travel the same distances as before the merger. Similarly, for counterfactual experiments concerning brewery fixed effects, we assume either that products get reassigned values of $\widetilde{K}_{bt}$ associated with their new breweries or that they retain the values of $\widetilde{K}_{bt}$ associated with their old pre-merger breweries. See Appendix E for more details. In total, given all the different combinations of post-merger scenarios, we conducted nine counterfactual experiments. Together with the original pre-merger scenario, this provides us with ten distinct environments for comparative analysis.

After calculating equilibrium market outcomes in each scenario, we use this data together with a simple fixed effects regression in order to decompose the effects. Specifically, we estimate the following equation:

$$\begin{aligned} MO_{ct}^{j} = a + b_s \mathbb{1}(\text{Scope}) + b_m \mathbb{1}(\text{Merger}) + b_{md} \mathbb{1}(\text{Merger}) \times \mathbb{1}(\text{New Distances}) + \\ + b_{mf} \mathbb{1}(\text{Merger}) \times \mathbb{1}(\text{New Brewery FEs}) + b_{ms} \mathbb{1}(\text{Merger}) \times \mathbb{1}(\text{Scope}) + \psi_{ct} + \psi_j + e_{ct}^{j} \end{aligned} \tag{23}$$

where MO_{ct}^{j} is the market outcome (marginal cost, price, or market share), and indicator variables are equal to one for observations associated with counterfactual experiments where this specific characteristic is turned on. For example, $\mathbb{1}(\text{Merger})$ equals one for all the post-merger counterfactuals. ψ_{ct} and ψ_j are market and product fixed effects, respectively.

Table 3 presents coefficients associated with the indicator variables in equation (23). As previously discussed, the impact of scope economies on market outcomes is substantial. Columns (3) and (4) suggest they lower the cost of merging parties by 28.8% and the cost of all the other firms by 36.2%. Moreover, scope economies contribute to lower costs and prices after the merger. The coefficients in front of the Merger $\times$ Scope interaction suggest an additional decrease of 7.4% in costs and a 4.3% reduction in prices for merging firms when scope economies are present. This effect can be attributed to a greater number of breweries producing a more diverse range of products due to the reallocation of production as a result of the merger. The reduction in shipping distances leads to similar effects. Moreover, the merger results in a significant share of production being reallocated towards more efficient breweries, which also contributes to lower costs and prices, as the coefficients associated with the Merger $\times$ New FEs interaction suggests.

However, all these cost savings are greatly attenuated due to the fragmentation of production and loss of scale at the brewery level. This is captured by the coefficient in front of the Merger indicator in column (3). This variable captures the remaining components of the merger's impact on costs. These include the cost increase resulting from a significant number of breweries of merged firms serving fewer markets post-merger (i.e., a decrease in the scale of production) and the increase in cost due to merged parties pulling back production in order to increase prices. In the end, the combined effect of the merger on costs is negative: as Table 3 suggests, the costs of the merged companies, on average, decrease by 6.5%. However, the average masks significant heterogeneity, which is even more evident when it comes to the effect on prices.

A lesson from this analysis is that while production fragmentation may create savings in shipping costs, it may create an inefficiency due to firms not fully benefiting from scope and scale economies. This insight may be relevant for future merger evaluations.

6 Concluding Remarks

We propose a new method to estimate economies of scale and scope suitable for applied work. Our method requires data commonly used for demand estimation (crucially, quantities produced and prices for each product–market combination) but does not require input data, making it easy to implement in other settings.

We apply our method to the US beer industry, which is an ideal setting to investigate the existence of scale and scope economies, as it features multiproduct firms and production that is consolidated in a small number of plants. Our estimates suggest the existence of both scale and scope economies. We find that shutting down economies of scope (i.e., no joint production takes place, but the production technology otherwise stays the same) would lead to price and marginal cost increases of 19.8 percent and 33.9 percent on average, respectively, decreasing market shares by 2.2 percent on average. Our findings suggest that scale and scope economies have a first-order effect in explaining productive efficiency in the US beer industry.

We also use our estimates to explore the implications of scale and scope economies for merger analysis using the MillerCoors joint venture. The antitrust investigation of the joint venture considered the tradeoff between two forces: the enhanced market power of MillerCoors and the transportation cost savings that would arise from the merged firm using a more geographically diversified network of production plants. We show that additional effects are relevant to consider: i) the enhanced market power of the merged firm leads to a decrease in the scale of production, which creates cost increases that at least partially offset the transportation cost savings; ii) the merged firm's plants gain scope economies as they produce more varieties following the merger (i.e., Coors and Miller beers are produced in all plants after the merger), which magnify the transportation cost savings caused by the merger. We find that these effects are as large as the transportation cost savings caused by the merger, making them key for understanding the competitive impact of the joint venture.

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A Properties of the Cost Function

Proof of Lemma 1

Proof. When $\phi > \alpha$, it follows that

$$C(\mathbf{Y}_i, \mathbf{A}_i, \mathbf{W}_i) < \sum_j C(\mathbf{Y}_i^j, \mathbf{A}_i, \mathbf{W}_i) \quad \Leftrightarrow$$

$$\left(\sum_j \left(\frac{Y_i^j}{A_i^j} \right)^{\frac{1}{\alpha}} \right)^{\alpha} < \left(\sum_j \left(\frac{Y_i^j}{A_i^j} \right)^{\frac{1}{\phi}} \right)^{\phi},$$

which holds true given that

$$\left(\sum_j \left(\frac{Y_i^j}{A_i^j} \right)^{\frac{1}{x}} \right)^{x}$$

is strictly increasing in x. A similar argument can be used to prove the other claims.

□

Statement and Proof of Lemma 2

Lemma 2 *Consider a vector $(Y_i^1, \ldots, Y_i^J)$ with $Y_i^j > 0$. Then,*

- *the marginal cost of product j is lower under joint production (with a strict inequality if $Y_i^k > 0$ for some $k \neq j$) when $\phi > \alpha$;*
- *the marginal cost of product j is grester under joint production (with a strict inequality if $Y_i^k > 0$ for some $k \neq j$) when $\alpha > \phi$.*

Proof. The marginal cost of production with joint and non-joint production is given by

$$\begin{aligned} MC_i^{\text{joint},j} &= \frac{1}{\phi} g(\mathbf{W}_i) \left(\sum_j \left(\frac{Y_i^j}{A_i^j} \right)^{\frac{1}{\alpha}} \right)^{\frac{\alpha}{\phi}-1} \left(\frac{Y_i^j}{A_i^j} \right)^{\frac{1}{\alpha}} \frac{1}{Y_i^j}, \\ MC_i^{\text{non-joint},j} &= \frac{1}{\phi} g(\mathbf{W}_i) \left(\frac{Y_i^j}{A_i^j} \right)^{\frac{1}{\phi}} \frac{1}{Y_i^j}, \end{aligned}$$

respectively, for $(Y_i^1, \ldots, Y_i^J) \geq 0$. When $\phi > \alpha$, it follows that

$$\begin{aligned}
MC_i^{\text{non-joint},j} &\geq MC_i^{\text{joint},j} && \Leftrightarrow \\
\left(\frac{Y_i^j}{A_i^j}\right)^{\frac{1}{\phi}} &\geq \left(\sum_j \left(\frac{Y_i^j}{A_i^j}\right)^{\frac{1}{\alpha}}\right)^{\frac{\alpha}{\phi}-1} \left(\frac{Y_i^j}{A_i^j}\right)^{\frac{1}{\alpha}} && \Leftrightarrow \\
1 &\geq \left(\left(\frac{Y_i^j}{A_i^j}\right)^{\frac{1}{\alpha}}\right)^{\frac{\phi-\alpha}{\phi}} \Big/ \left(\sum_j \left(\frac{Y_i^j}{A_i^j}\right)^{\frac{1}{\alpha}}\right)^{\frac{\phi-\alpha}{\phi}},
\end{aligned}$$

where the inequality is strict if $Y_i^k > 0$ for some $k \neq j$. When $\phi < \alpha$, it is straightforward to establish that the reverse inequality holds. □

B A Model of Public and Private Tasks

In this Appendix, we derive the cost function (3) for the special case of Cobb-Douglas production.[16] To simplify notation, we suppress time subscripts and consider a single firm/brewery, so that we can replace $b(i) = i$.

For each input X, there are two tasks- a private task r, and a public task p. A firm allocates X_i^{rj} units of X to product line j doing the private task (e.g. construction), and X_i^p units of X to the public task (supervising), which affects all product lines at once. Output of product line j is determined by the following production function

$$Y_i^j = \frac{A_i^j}{C}\left(\prod_X \left(X_i^{rj}\right)^{\beta_X^r} \left(X_i^p\right)^{\beta_X^p}\right) \tag{24}$$

Where $C \equiv \frac{\prod_X \left(\beta_X^r\right)^{\beta_X^r} \left(\beta_x^P\right)^{\beta_X^p}}{\prod_X \left(\beta_X^r + \beta_X^p\right)^{\beta_X^r + \beta_X^p}}$.

We assume that firms choose the allocation of inputs across tasks, given $\mathbf{X}_i$ to produce the maximal quantities of output feasible; i.e. the firm always operates on their production possibilities frontier. One way to characterize the solution to this problem is by solving for a firm's *output distance function* (Shephard 1970, Caves et al. 1982), which tells us the minimum amount a firm must scale down a given output vector $\mathbf{Y}_{ibt}$ to make sure that $(\frac{\mathbf{Y}_{ibt}}{\delta}, \mathbf{X}_{ibt}) \in \mathbb{P}_{ibt}$, where $\mathbb{P}_{ibt}$ is the firm's production possibility set, and δ is the minimized scaling factor. For this particular production problem, the firm's output distance function is given by:

[16] For more general specifications of the technology, see Cairncross et al. (2023).

$$
\begin{aligned}
D\left(\mathbf{Y}_i, \mathbf{X}_i, \mathbf{A}_i\right) \equiv \min_{\delta, \mathbf{X}_i, \{\mathbf{X}_i^{rj}\}_j} \quad & \delta \\
\text{s.t.:} \quad & \frac{Y^j}{\delta} \leq \frac{A_i^j}{C}\left(\prod_X \left(X_i^{rj}\right)^{\beta_X^r}\left(X_i^p\right)^{\beta_X^p}\right) \ \forall j \\
& X_i^p + \sum_j X_i^{rj} \leq X_i, \ \forall X
\end{aligned} \tag{25}
$$

This optimization problem has the following Lagrangian

$$
L = \delta + \sum_j \lambda_i^j \left(\frac{Y_{it}^j}{\delta} - \frac{A_i^j}{C}\left(\prod_X \left(X_i^{rj}\right)^{\beta_X^r}\left(X_i^p\right)^{\beta_X^p}\right)\right) + \sum_X \mu_X \left(\sum_j X_i^{rj} + X_i^p - X_i\right) \tag{26}
$$

Since the production functions are increasing in all inputs, all constraints will bind with equality, and therefore $\lambda_i^j > 0 \ \forall j$ and $\mu_X > 0 \ \forall X$, with:

$$
\frac{Y^j}{\delta} = \frac{A_i^j}{C}\left(\prod_X \left(X_i^{rj}\right)^{\beta_X^r}\left(X_i^p\right)^{\beta_X^p}\right) \quad \forall j \tag{27}
$$

and

$$
X_i^p + \sum_j X_i^{rj} = X_i \quad \forall X \tag{28}
$$

Taking the first order condition for X_i^{rj} yields

$$
\lambda_i^j \beta_X^r \frac{\frac{A_i^j}{C}\left(\prod_X \left(X_i^{rj}\right)^{\beta_X^r}\left(X_i^p\right)^{\beta_X^p}\right)}{X_i^{rj}} = \lambda_i^j \beta_X^r \frac{\frac{Y_i^j}{\delta}}{X_i^{rj}} = \mu_X \tag{29}
$$

The first order condition for X_{it}^p satisfies

$$
\sum_j \lambda_i^j \beta_X^p \frac{\frac{A_i^j}{C}\left(\prod_X \left(X_i^{rj}\right)^{\beta_X^r}\left(X_i^p\right)^{\beta_X^p}\right)}{X_i^p} = \frac{\beta_X^p}{\delta X_i^p}\sum_j \lambda_i^j Y_i^j = \mu_X \tag{30}
$$

Let $X_i^r \equiv \sum_j X_i^{rj}$. Rearrange and sum (29) for all j, yielding:

$$
\mu_X X_i^r = \frac{\beta_X^r}{\delta}\sum_j \lambda_i^j Y_i^j \tag{31}
$$

Rearrange (30) and divide by (31)

$$
\frac{X_i^p}{X_i^r} = \frac{\beta_X^p}{\beta_X^r} \tag{32}
$$

Since $X_i = X_i^r + X_i^p$, substitute (32) into this expression, yielding:

$$X_i^r + \frac{\beta_X^p}{\beta_X^r} X_i^r = X_i$$

or:

$$X_i^r = \frac{\beta_X^r}{\beta_X^r + \beta_X^p} X_i \tag{33}$$

and:

$$X_i^p = \frac{\beta_X^p}{\beta_X^r + \beta_X^p} X_i \tag{34}$$

Next, rearrange (29) and divide by (31), yielding:

$$X_i^{rj} = \frac{\lambda_i^j Y_{it}^j}{\sum_k \lambda_i^k Y_i^k} X_i^r \tag{35}$$

Substitute into (33), (34) and (35) into (27), which yields :

$$\frac{Y_i^j}{\delta} = \frac{A_i^j}{C} \left(\prod_X \left(\frac{\lambda_i^j Y_i^j}{\sum_k \lambda_i^k Y_i^k} \frac{\beta_X^r}{\beta_X^r + \beta_X^p} X_i \right)^{\beta_X^r} \left(\frac{\beta_X^p}{\beta_X^r + \beta_X^p} X_i \right)^{\beta_X^p} \right)$$

Define $\alpha \equiv \sum_X \beta_X^r$, $\beta_X = \beta_X^r + \beta_X^p$, and $\phi \equiv \sum_X \beta_X$. Rearranging and cancelling out terms in the above yields::

$$\left(\frac{Y_i^j}{\delta A_i^j} \right)^{\frac{1}{\alpha}} = \frac{\lambda_i^j Y_i^j}{\sum_k \lambda_i^k Y_i^k} \left(\prod_X (X_i)^{\beta_X} \right)^{\frac{1}{\alpha}}$$

Sum over all j :

$$\frac{1}{\delta^{\frac{1}{\alpha}}} \sum_j \left(\frac{Y_i^j}{A_i^j} \right)^{\frac{1}{\alpha}} = \left(\prod_X (X_i)^{\beta_X} \right)^{\frac{1}{\alpha}}$$

Or:

$$\delta = \frac{\left(\sum_j \left(\frac{Y_i^j}{A_i^j} \right)^{\frac{1}{\alpha}} \right)^{\alpha}}{\prod_X (X_i)^{\beta_X}}$$

This establishes that the firm's distance function is $D\left(\mathbf{Y}_i, \mathbf{X}_i, \mathbf{A}_i\right) = \frac{\left(\sum_j \left(\frac{Y_i^j}{A_i^j}\right)^{\frac{1}{\alpha}}\right)^{\alpha}}{\prod_X (X_i)^{\beta_X}}$.[17]

Assuming that a firm operates on its production possibility frontier (i.e., does not waste any inputs when producing some desired output vector $\mathbf{Y}_i$) means that the firm will only $(\mathbf{Y}_i, \mathbf{X}_i)$ satisfying $D_{it}\left(\mathbf{Y}_{it}, \mathbf{X}_{it}\right) = 1$. This implies that

$$\frac{\left(\sum_j \left(\frac{Y_i^j}{A_i^j}\right)^{\frac{1}{\alpha}}\right)^{\alpha}}{\prod_X \left(X_i\right)^{\beta_X}} = 1 \tag{36}$$

To generate the relevant cost function, it is useful to rearrange (36) as follows:

$$\mathbb{Y}_i \equiv \left(\sum_{j \in \mathbb{B}_i} \left(\frac{Y_i^j}{A_i^j}\right)^{\frac{1}{\alpha}}\right)^{\alpha} = \prod_X \left(X_i\right)^{\beta_X} \tag{37}$$

Equation (37) provides a "psuedo" Cobb-Douglas production function for the output aggregator $\mathbb{Y}_i \equiv \left(\sum_j \left(\frac{Y_i^j}{A_i^j}\right)^{\frac{1}{\alpha}}\right)^{\alpha}$. Under the further assumption that all inputs $\mathbf{X}_i$ are obtained from perfectly competitive markets at prices $\mathbf{W}_i^X$, then it is well known that the cost function for (37) is given by

$$C(\mathbb{Y}_i, \mathbf{W}_i) = \underbrace{K \left(\prod_X \left(W_i^X\right)^{\frac{\beta_X}{\sum \beta_X}}\right)}_{\equiv g(\mathbf{W}_i)} \left(\mathbb{Y}_i\right)^{\frac{1}{\phi}} \tag{38}$$

where K is a constant that depends on the various β_X terms.

Substituting the definition of the output aggregator $\mathbb{Y}_i \equiv \left(\sum_j \left(\frac{Y_i^j}{A_i^j}\right)^{\frac{1}{\alpha}}\right)^{\alpha}$ into (39) this expression then yields:

$$C(\mathbf{Y}_i, \mathbf{A}_i, \mathbf{W}_i) = g(\mathbf{W}_i) \left(\sum_j \left(\frac{Y_i^j}{A_i^j}\right)^{\frac{1}{\alpha}}\right)^{\frac{\alpha}{\phi}} \tag{39}$$

Note that from this derivation of the firm's cost function, we can see that α, which we defined as $\alpha \equiv \sum_X \beta_X^r$, should be interpreted as the share of *rival* or *private* inputs in production, while overall returns to scale, $\phi \equiv \sum_X \beta_X$ depends both private and public tasks, so $\alpha \leq \phi$.

[17] While we did not use the first order condition for δ, which implies $\delta^2 = \sum_j \lambda_i^j Y_i^j$, we would use this expression to solve for μ_X and λ_i^j

C S_{bt}^{j} is the share of rival inputs allocated to product j

Define $S_{bt}^{j} \equiv \frac{\sum_{c\in\mathbb{C}_{bt}^{j}} MC_{ct}^{j}Q_{ct}^{j}}{\sum_{k\in\mathbb{J}_{bt}}\sum_{c\in\mathbb{C}_{bt}^{k}} MC_{ct}^{k}Q_{ct}^{k}}$ as in the main text. In this appendix, we now show that this share is equal to the share of inputs allocated to the rival task for good j, i.e. $S_{bt}^{j} = \frac{X_{bt}^{rj}}{\sum_{k\in\mathbb{J}_{bt}} X_{bt}^{rk}} = \frac{X_{bt}^{rj}}{X_{bt}^{r}}\ \forall X$.

The result can be obtained by noting that the relevant rival input shares were already determined when we characterized a firm's output distance function in Appendix B; specifically, equation (35) tells us that $\frac{X_{bt}^{rj}}{X_{bt}^{r}} = \frac{\lambda_{bt}^{j}Y_{bt}^{j}}{\sum_k \lambda_i^k Y_{bt}^{k}}$, where we now let $i=(b,t)$. We can obtain the desired result by showing that $\lambda_{bt}^{j}Y_{bt}^{j}$ is proportional to $\sum_{c\in\mathbb{C}_{bt}^{j}} MC_{ct}^{j}Q_{ct}^{j}$; this can be done by applying the envelope theorem to a firm's cost minimization problem, as well as the output distance function problem.

First, note that a firm's cost function can be recovered from the following cost minimization problem:

$$\begin{aligned} C\left(\mathbf{Q}_{bt},\mathbf{A}_{bt},\mathbf{W}_{bt},\tau_{bt}\right) \equiv & \min_{\mathbf{X}_i} \sum_X W_i^X X_i \\ & \text{s.t.: } D(\mathbf{Q}_{bt},\mathbf{A}_{bt},\mathbf{W}_{bt},\tau_{bt}) \leq 1 \end{aligned} \tag{40}$$

where $D(\mathbf{Q}_{bt},\mathbf{A}_{bt},\mathbf{W}_{bt},\tau_{bt})$ is the output distance function corresponding to the cost function used in the main text.[18]

This problem has the following Lagrangian:

$$L = \sum_X W_{bt}^X X_{bt} + \theta_{bt}(D(\mathbf{Q}_{bt},\mathbf{A}_{bt},\mathbf{W}_{bt},\tau_{bt}) - 1)$$

From the envelope theorem, it follows that:

$$MC_{ct}^{j} \equiv \frac{\partial C(\mathbf{Q}_{bt},\mathbf{A}_{bt},\mathbf{W}_{bt},\tau_{bt})}{\partial Q_{ct}^{j}} = \theta_{bt}\frac{\partial D(\mathbf{Q}_{bt},\mathbf{A}_{bt},\mathbf{W}_{bt},\tau_{bt})}{\partial Q_{ct}^{j}} \tag{41}$$

From Appendix B, we know that the cost function used in the main text has an output distance function defined by (40). Applying the envelope theorem to its associated Lagrangian (equation 26) yields:

[18]Note that we have written the output distance function in terms of quantities sold in each market c that are produced by brewery b, $\mathbf{Q}_{bt}$. Since $D\left(\mathbf{Y}_b,\mathbf{X}_b,\mathbf{A}_b\right) = \frac{\left(\sum_j \left(\frac{Y_b^j}{A_b^j}\right)^{\frac{1}{\alpha}}\right)^{\alpha}}{\prod_X (X_b)^{\beta_X}}$ from Appendix B, this becomes $D\left(\mathbf{Q}_{bt},\mathbf{A}_{bt},\mathbf{W}_{bt},\tau_{bt}\right) = \frac{\left(\sum_j \left(\frac{\sum_c Q_{ct}^j \tau_{bct}^j}{A_i^j}\right)^{\frac{1}{\alpha}}\right)^{\alpha}}{\prod_X (X_b)^{\beta_X}}$ once we replace aggregate factory-level outputs with market-specific sales through the iceberg transportation constraint (4).

$$\frac{\partial D(\mathbf{Q}_{bt},\mathbf{A}_{bt},\mathbf{W}_{bt},\tau_{bt})}{\partial Q^j_{ct}} = \frac{\partial D(\mathbf{Q}_{bt},\mathbf{A}_{bt},\mathbf{W}_{bt},\tau_{bt})}{\partial Y^j_{bt}} \frac{\partial Y^j_{bt}}{\partial Q^j_{ct}} = \frac{\lambda^j_{bt}}{\delta}\tau^j_{bct} = \lambda^j_{bt}\tau^j_{bct} \tag{42}$$

where the third equality uses (4), and the fourth equality uses the fact that $\delta = 1$ when firms cost minimize.

Note that (41) and (42) together imply that:

$$MC^j_{ct}Q^j_{ct} = \theta_{bt}\frac{\partial D(\mathbf{Q}_{bt},\mathbf{A}_{bt},\mathbf{W}_{bt},\tau_{bt})}{\partial Q^j_{ct}}Q^j_{ct} = \theta_{bt}\tau^j_{bct}\lambda^j_{bt}Q^j_{ct} \tag{43}$$

Summing over all $c \in \mathbb{C}^j_{bt}$ then yields:

$$\sum_{\in\mathbb{C}^j_{bt}} MC^j_{ct}Q^j_{ct} = \theta_{bt}\lambda^j_{bt}\sum_{\in\mathbb{C}^j_{bt}}\tau^j_{bct}Q^j_{ct} = \theta_{bt}\lambda^j_{bt}Y^j_{bt} \tag{44}$$

where the last equality follows from (4).

Substituting equation (44) into (35) then yields:

$$\frac{X^{rj}_{bt}}{X^r_{bt}} = \frac{\lambda^j_{bt}Y^j_{bt}}{\sum_{k\in\mathbb{J}_{bt}}\lambda^k_i Y^k_{bt}} = \frac{\frac{\sum_{\in\mathbb{C}^j_{bt}} MC^j_{ct}Q^j_{ct}}{\theta_{bt}}}{\sum_{k\in\mathbb{J}_{bt}}\frac{\sum_{\in\mathbb{C}^k_{bt}} MC^k_{ct}Q^k_{ct}}{\theta_{bt}}} = \frac{\sum_{c\in\mathbb{C}^j_{bt}} MC^j_{ct}Q^j_{ct}}{\sum_{k\in\mathbb{J}_{bt}}\sum_{c\in\mathbb{C}^k_{bt}} MC^k_{ct}Q^k_{ct}} = S^j_{bt} \tag{45}$$

D Estimates of Demand Parameters

We use the estimates of the demand parameters directly from Miller and Weinberg (2017). Specifically, we use the estimates from their baseline RCNL-1 model (see Table IV in Miller and Weinberg (2017)).

Variables	**Parameter**	**Estimate**
Price	γ	-0.0887
Nesting Parameter	ϱ	0.8299
Demographic interactions		
Income $\times$ Price	Π_1	0.0007
Income $\times$ Constant	Π_2	0.0143
Income $\times$ Calories	Π_3	0.0043

E Decomposition of K_{bt}

Recall that $K_{bt} = g(\mathbf{W}_{bt})/(\phi\Omega_{bt}^{\frac{1}{\phi}})$. At the same time, Ω_{bt} is, in fact, a location-level average of product-market pair productivity terms with $\ln \Omega_{bt} = \frac{1}{\sum_{j\in\mathbb{J}_{bt}} |\mathbb{C}^j_{bt}|} \sum_{j\in\mathbb{J}_{bt}} \sum_{c\in\mathbb{C}^j_{bt}} \ln \Omega^j_{bct}$. That should be taken into account when reallocating products across locations. In other words, when reallocating product j from location b to location b', $K_{b't}$ assigned to this product and other products made in location b' will change through the change in the average productivity term.

To account for that, we follow the assumption that the productivity term $\ln A^j_{bt}$ is a sum of product and location-specific shocks (same assumption that we use in equation (21) when estimating the relationship between productivity and transportation cost). Then we can rewrite $\Omega^j_{bct} \equiv A^j_{bt}/\tau^j_{bct}$ in the following way:

$$\ln \Omega^j_{bct} = \ln A^j_t + \ln A_{bt} - \ln \tau^j_{bct} \tag{46}$$

That allows us to rewrite the equation for K_{bt} in the following way:

$$\ln K_{bt} + \left(\frac{1}{\phi} \frac{1}{\sum_{j\in\mathbb{J}_{bt}} |\mathbb{C}^j_{bt}|} \sum_{j\in\mathbb{J}_{bt}} \sum_{c\in\mathbb{C}^j_{bt}} (\ln A^j_t - \ln \tau^j_{bct}) \right) = \underbrace{\ln g(\mathbf{W}_{bt}) - \ln \phi - \frac{1}{\phi} \ln A_{bt}}_{\equiv \ln \widetilde{K}_{bt}}, \tag{47}$$

where $\widetilde{K}_{bt}$ captures the variation in productivity and input prices across production locations. Notice that after estimating K_{bt} and ϕ using equation (15), and τ^j_{bct} and A^j_t using equation (21), we can calculate $\widetilde{K}_{bt}$ using the equation above.

When product l is reallocated from location b to location b', we can recalculate the new $K_{b't}$ associated with this product in the following way:

$$\ln K_{b't} = \ln \widetilde{K}_{b't} - \left(\frac{1}{\phi} \frac{1}{\sum_{j\in\mathbb{J}_{b't}} |\mathbb{C}^j_{b't}|} \sum_{j\in\mathbb{J}_{b't}} \sum_{c\in\mathbb{C}^j_{b't}} (\ln A^j_t - \ln \tau^j_{b'ct}) \right), \tag{48}$$

where $\mathbb{J}_{b't}$ will include the product l and all other products made in location b'. In some counterfactuals that we implement for the merger analysis, $\widetilde{K}_{bt}$ is not changed to $\widetilde{K}_{b't}$ (counterfactuals without changing the brewery-level productivities or fixed effects); in some counterfactuals, the distance that product l has to travel is not changed, which will be affecting the average distance component in $K_{b't}$. However, in all the merger counterfactuals, the production set for product l across which product-level productivities and transportation costs are averaged changes from $\mathbb{J}_{bt}$ to $\mathbb{J}_{b't}$.

Finally, notice that the transportation cost includes a location-product-market specific unobserved component $\widetilde{\tau}_{bct}^{j}$ which incorporates all the other factors that affect the cost of delivering product j from location b to market c. Since these factors are not included in our model, we remove this component before calculating the counterfactuals. We also recalculate the equilibrium of the original (pre-merger) environment without this component and use these results when comparing the outcomes.