Mergers, Brand Competition, and the Price of a Pint

by

Joris Pinkse and Margaret E. Slade

Department of Economics
University of British Columbia
Vancouver, BC V6T 1Z1
Canada
Email: slade@econ.ubc.ca

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Abstract:

Mergers in the UK brewing industry in the last decade have reduced the number of national brewers from six to four. The number of brands, in contrast, has remained relatively constant. We analyze the effects of the mergers on brand competition and pricing. Brand–level demand equations are estimated from a panel that includes all draft beers that accounted for at least 1/2% of local markets. We model brand–substitution possibilities in a very flexible way. In particular, we estimate the matrix of cross–price elasticities nonparametrically. We use the estimated demand equations to assess the strength of brand competition along various dimensions, and we evaluate the effects of the mergers by computing equilibria of pricing games with different numbers of players.

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1 Introduction

Historically, the brewing industry in the UK developed in a very different fashion from those in, for example, the US, Canada, and France, which were dominated by a few large brewers that sold rather homogeneous national brands of lagers. Indeed, the UK industry, which was relatively unconcentrated, produced a large variety of ales, and regional variation in product offerings was substantial. Moreover, national advertising played a less important role than in many other countries. In the last decade, however, there have been a succession of successful mergers that have increased concentration in brewing, as well as proposed mergers that, if successful, would have added to that trend.[1] It is thus natural to ask how those mergers have changed both product pricing and product offerings. In particular, the mergers could have resulted in higher prices, a reduction in the number of brands produced, an increase in brand uniformity, and a move towards competition through national advertising rather than through product differences.

In this paper, we use panel data on all brands of beer that constitute at least one half of one percent of a regional market to evaluate the mergers. We estimate demand equations for brands of draft beers sold in two regions of the country (Greater London and Anglia) in two bimonthly time periods (Aug/Sept and Oct/Nov 1995) and in two types of public houses (multiples and independents). We model substitution possibilities among brands using a technique that was developed in Pinkse, Slade, and Brett (1998) to deal with differentiated products.[2] In particular, we estimate the matrix of cross–price elasticities nonparametrically as a function of a number of measures of the distance between brands in product–characteristic space. We then use our estimated demand equations, together with engineering data on costs, to evaluate the game that the brewers are engaged in. Finally, we evaluate the effects of the mergers on prices by solving for the equilibria of games with different numbers of players. In other words, we undo a merger by allowing the prices of the merged brands to be chosen by two separate players that correspond to the pre–merger configuration, and we assess proposed mergers by performing the reverse exercise — by allowing a single player to choose the prices of all brands brewed by the merger partners.

The organization of the paper is as follows. In the next section, we set the stage by describing the structure of the UK brewing industry and contrasting it with the situation that prevails in other countries. We also look at recent decisions of the UK Monopolies and Mergers Commission (MMC) that have affected the structure of the industry. These include the 'Beer Orders' of 1989 that changed the structure of the downstream or retailing sector, as well as decisions involving mergers in the upstream or brewing sector.

[1] Courage and Grand Met merged to form Courage, Allied Lyons and Carlsberg merged to form Carlsberg–Tetley, and the merged Courage merged with Scottish & Newcastle to form Scottish Courage. In addition, a merger between Bass and Carlsberg–Tetley was attempted, which would have further reduced the number of national brewers to three.

[2] The application in that paper involves products that are differentiated in geographic space, whereas the application in this paper involves differentiation in product–characteristic space.

Section 3 contains a brief review of the literature that attempts to model differentiated products both theoretically and empirically. It also contrasts our method of assessing the demand for branded products with those that are commonly used by other researchers.

Section 4 presents our model of the demand for brands by heterogeneous individuals.[3] Each consumer has an ideosyncratic utility function, which we approximate with a functional form that has two important characteristics: it places no restrictions on brand substitution possibilities, and it satisfies the restrictions that are required for exact aggregation across individuals. Demands for brands are obtained by partially differentiating the aggregate utility function with respect to prices. We allow each cross–price elasticity in the resulting system of demand equations to depend on a number of measures of the distance between brands in product–characteristic space, and we estimate the functional form of that dependence. Finally, we discuss how one can use the estimated demand equations to evaluate the game that the brewers play.

Section 5 discusses our estimation technique. We use a series expansion to approximate the function of the distance measures that determines the cross–price elasticities. Furthermore, since the prices of all brands are, at least potentially, jointly determined and thus endogenous, we use an instrumental–variables semiparametric technique.

Section 6 presents the data and discusses our choice of measures of distance in product–characteristic space, whereas sections 7 and 8 contain our econometric estimates of demand and our assessment of equilibrium in the market. Finally, section 9 discusses solutions to the merger games. To anticipate, we fail to reject a Bertrand–pricing game among the brewers. Furthermore, we find that the Scottish–Courage merger had little effect on prices, whereas a merger between Bass and Carlsberg–Tetley would have resulted in more substantial price increases.

2 The UK Beer Market

2.1 International Comparisons

Although beer markets have certain features in common across countries, cross–country differences are also striking. To get a feel for the UK industry, it is therefore useful to begin with international comparisons. Table 1 summarizes some of the differences between the UK, US, Canada, France, and Germany.

The first part of table 1 shows that, when it comes to beer consumption per head and the fraction of beer sales that originate abroad, the UK lies between France and Germany, with Germany having higher per capita consumption and France relying more heavily on imports. Consumers in the US and Canada, who are similar to each other, drink less beer per capita and consume fewer imports than their counterparts in the UK. Finally, over time, per capita beer consumption has fallen in most countries, whereas imports have risen.

[3] This section differs from Pinkse, Slade, and Brett (1998), where derived rather than consumer demand is assessed.

Whereas the UK is not an outlier with respect to the statistics contained in table 1A, it is clearly different from the other countries with respect to the ratio of draft to total beer sales, as can be seen in table 1B. Indeed, draft sales in the UK accounted for almost three times the comparable percentages in France and Germany and about six times the percentages in North America. In all countries, however, draft's fraction has fallen, as more beer has been consumed at home. Table 1B also shows that UK beers are of lower strength than those from the other countries, which is due to the fact that more ale and less lager is consumed, and lagers tend to be stronger.

Turning to production, table 1C compares one important aspect of the industry — its concentration, or lack thereof, into the hands of a small number of brewers.[4] The UK industry is clearly less concentrated than its counterparts in the US, Canada, and France, where beer tends to be mass produced. Production in Germany, in contrast, where specialty beers predominate, is much less concentrated. It thus seems that brand heterogeneity and an unconcentrated brewing sector go hand in hand.

2.2 The UK Industry

The UK beer industry has undergone substantial changes in both production and consumption in the last few decades, some of which are summarized in table 2. Beers can be divided into three broad categories: ales, stouts, and lagers. Although UK consumers have traditionally preferred ales to lagers, the consumption of lager has increased at a steady pace. Indeed, from less than 1% of the market in 1960 (not shown in the table), lager became the most popular drink in 1990, with sales exceeding the sum of ale and stout, and its popularity continues to grow. Most UK lagers bear the names of familiar non–British beers such as Budweiser, Fosters, and Kronenbourg. Almost all, however, are brewed under license in the UK and are therefore not considered imports.

A second important aspect of beer consumption is the popularity of 'real' or cask–conditioned ale. Real products are alive and undergo a second fermentation in the cask, whereas keg and tank products are sterilized. The statistics in table 2, however, which show real ale's market share increasing, must be interpreted with caution since they show percentages of the ale market. As a percentage of the total beer market, which includes lager, real products have lost ground.

The final trend in consumption is the decline in on–premise sales. On–premise consumption includes sales in bars, hotels, and clubs, whereas off–premise consumption refers to beer that is purchased in a store and consumed at home, out of doors, or in nonlicensed establishments. Clearly, draft sales are a subset of on–premise consumption, since some packaged products are consumed in licensed establishments.

With respect to production, table 2 shows that the number of brewers has declined steadily. Indeed, in 1900, there were nearly 1,500 brewery companies (not shown in the table), but this number fell during the century and is currently about sixty. However, in addition to incorporated brewers, there are approximately 200

[4] With the exception of Germany, the table shows three–firm concentration ratios. Any other concentration measure, however, would tell the same story.

microbreweries operating at very small scales. In fact, most brewers are small, and few produce products that account for more then 1/2% of local markets.[5]

This snapshot of the UK beer industry shows significant changes in tastes and consumption habits as well as a decline in the number of companies that cater to those tastes. Nevertheless, as we have seen, compared to many other countries, the UK brewing sector was only moderately concentrated. Recent developments in the industry, however, have resulted in substantial changes in ownership patterns.

2.3 Public Policy Towards the UK Beer Industry

It is not unusual for the beer industry to attract the attention of politicians and civil servants. Government involvement in the industry stems from four concerns: the social consequences of alcohol consumption, the revenue obtained from alcohol sales, the level of concentration in the brewing sector, and the extent of brewer control over retailing. In recent years, moreover, public scrutiny of the industry has accelerated. Indeed, there have been over thirty reviews by UK and European Union authorities since the 1960s. Many of those investigations were triggered by proposed mergers in the industry. Several, however, were more general assessments of prices, profits, and tied sales.[6]

For our analysis, four mergers, three actual and one proposed, are of primary interest. These are the successful mergers between Courage and Grand Metropolitan (Grand Met) in 1990, Allied Lyons and Carlsberg in 1992, and Courage and Scottish & Newcastle (S&N) in 1995, and the proposed merger between Bass and Carlsberg–Tetley (CT) that was denied in 1997. It is difficult to discuss the positions taken by the Monopolies and Mergers Commission (MMC) and Office of Fair Trading (OFT) with respect to the mergers, however, without a brief discussion of their views on the links between brewers and their retail outlets.

2.3.1 The Beer Orders

Prior to the late 1980s, a large fraction of UK public houses (pubs) were owned by brewers and operated under exclusive–purchasing agreements (ties) that limited the pubs to selling brands that were produced by their affiliated brewer.[7] Public officials have long been concerned that those tying arrangements would somehow extend the market power that they perceived in the upstream or brewing sector to the downstream or retailing sector. Absent the system of ties, they believed that retailing would be competitive.

In the late 1980's, the OFT requested the MMC to undertake a major industry review. The product of that investigation was the 500–page MMC report entitled

[5] In the greater London area, there are only 10 companies that produce brands whose sales are as large as 1/2%, whereas in Anglia the comparable number is 9.

[6] For an analysis of tied sales in the UK brewing sector, see Slade (1998).

[7] Such tying arrangements are illegal in the US. See Slade (1999) for a discussion of the legal differences.

"The Supply of Beer," which appeared in February of 1989. The MMC recommended measures that eventually led brewers to divest themselves of 14,000 public houses. The Commission claimed that their recommendations would lower retail prices and increase consumer choice. There has been considerable doubt, however, that their objectives were achieved. Indeed, after divestiture, retail beer prices actually rose (Slade 1998).

The MMC report is unclear about the economic reasoning that led to the decision to force divestiture. Nevertheless, the MMC alleged that, due to high concentration, the brewers possessed market power and their involvment in retailing protected that power.

2.3.2 The Mergers

After the Beer Orders, the brewing industry became more concentrated. Increases in brewing–market concentration were due to mergers, which the MMC allowed, as well as to the fact that some firms (e.g. Boddingtons) ceased brewing, whereas others (e.g. Courage) ceased retailing. Nevertheless, the MMC continues to favor recommendations that focus on the retail sector and the vertical linkages between brewers and public houses, in spite of their claim that the source of monopoly power lies in brewing. The discussion below illustrates the position that the MMC has taken.

The Courage/Grand Met Merger: The merger between Courage and Grand Met that occurred in 1990, just after the Beer Orders were passed, reduced the number of national brewers from six to five.[8] This event was complex. However, the details are unimportant. Briefly, Grand Met sold its brewing interests to Courage and ceased operating in the upstream market, whereas Courage sold its public houses to Grand Met and ceased operating in the downstream market.[9] In addition, Courage was given an exclusive contract to supply Grand Met's pubs. At the time of the merger, Grand Met controlled 11% of the beer market, whereas Courage controlled 9%. The merger transformed Courage into the second largest producer, just behind Bass, which had a market share of 22%. Nevertheless, three of the four MMC recommendations involved the tied estate rather than increases in brewing concentration *per se.*

The Allied Lyons/Carlsberg Joint Venture: In 1992, Allied Lyons, a British food company that owned breweries, formed a joint venture with Carlsberg, a Danish brewer. Their combined brewing assets, which were renamed Carlsberg–Tetley, became jointly owned by the two parents. At the time of the joint venture, Allied Lyons controlled 12% of the beer market, whereas Carlsberg controlled 4%. Their shares of the lager market, however, were higher, with 8 and 13%, respectively. The joint venture became the third largest brewer, behind Bass and Courage. The number of national brewers, however, was unchanged, since Carlsberg was not one of them.

[8] Courage is itself owned by Fosters, an Australian company.

[9] More precisely, some of the former public houses of both Courage and Grant Met became jointly owned by Grand Met and Elders, whereas others became owned by Inntrepreneur, which was in turn owned by Grant Met and Courage and managed by Grand Met.

The MMC was principally concerned with the fact that Carlsberg was one of a very few brewers without a tied estate.[10] Indeed, prior to the merger, over half of Carlsberg's sales went to Courage and S&N. As a consequence, all three of the MMC's recommendations involved vertical linkages between CT and the retail sector.

The Courage S&N Merger: In 1995, the merged firm Courage merged again with Scottish & Newcastle. This event, which reduced the number of national brewers from five to four, created the largest brewer in the UK. The combined firm, with a market share of 28%, was substantially larger than Bass, which had a market share of 23% and thus dropped from number one to two. In spite of the fact that the majority of the groups that were asked to comment on the merger favored a full investigation by the MMC, the OFT did not refer the matter to the MMC. Instead, it allowed the merger to proceed subject to a number of undertakings, all of which involved the tied estate.[11] The OFT rejected the idea of divestiture of breweries or brands but instead favored *"the alternative remedy that has generally been adopted following previous references ... to weaken the extent of vertical links with the merged company."* (DGFT, 1995, p.3).

The Bass/CT Merger: The fourth and largest merger was proposed in 1997 but not consummated. This involved the numbers two and three brewers, Bass and Carlsberg–Tetley, and would have created a new firm, BCT, with an overall market share of 37%. Moreover, it would have further reduced the number of national brewers from four to three. At the time, Bass controlled 23% of the beer market, CT controlled 14%, and Scottish Courage, which would have become the second largest firm, had a market share of 28%. The MMC estimated that, after the merger, the Hirshman/Herfindahl index of concentration (HHI) would rise from 1,678 to 2,332. Furthermore, it noted that the US Department of Justice's 1992 Merger Guidelines specify that a merger should raise concerns about competition if the post–merger HHI is over 1,800 and the change in the HHI is at least 50 points. Nevertheless, the MMC recommended that the merger be allowed to go forward.[12] We quote from their recommendations to illustrate their concern with vertical linkages at the expense of horizontal concentration.

> *The proposed merger would lead to some net efficiency gains which would not be achieved in the absence of the merger. But in our judgment these benefits would not be sufficient to outweigh the adverse effects we have identified. The majority of us believe that it is possible to remedy the adverse effects of the proposed merger with measures designed to counteract the increase in Bass's market power. To that end we recommend a pack-*

[10] Brewers without tied estates are not vertically integrated into retailing and have no exclusive–purchasing agreements.

[11] After the earlier merger with Allied Lyons, unlike S&N, Courage did not have a tied estate. Nevertheless, it had exclusive–supply contracts with Inntrepreneur (see footnotenote 9).

[12] The one economist on the Commission, David Newbery, wrote a dissenting opinion.

age of remedies involving a reduction in the number of Bass's tied houses to a maximum of 2,500 (MMC 1997, p. 3).

In spite of the MMC's favorable recommendation, the BCT merger was not consummated because the president of the Board of Trade did not accept the MMC's advice.

Table 3 summarizes the market shares of each firm before and after each merger. One can see that, a few years after a merger, the merged firm's market share is less than the sum of the premerged shares, which could mean that increased efficiency does not overwhelm increased market power. Figure 1 shows the chronology of the important merger events in the industry.

3 Related Literature

3.1 Theoretical Models of Differentiated–Products

In any market where price is posted and transactions occur at posted prices, price is the obvious strategic variable. Most retail markets fit this description. There are, however, many varieties of pricing games, and each is associated with a set of predictions about the structure of the market and the nature of the rivalry within that market.

With one–dimensional–spatial models, whether linear (Hotelling 1929), circular (Salop 1979), or vertical (Gabszewicz and Thisse 1979), each firm competes directly only with its two neighbors, one on either side. In other words, conditional on neighbor prices, fluctuations in prices of more distant competitors have no effect on own sales.[13] In equilibrium, however, prices of more distant competitors can have an indirect effect when they cause changes at neighboring locations.

In direct contrast to spatial models, where competition is local, models of monopolistic competition in the spirit of Chamberlin (1933) (e.g., Spence 1976 and Dixit and Stiglitz 1977) are based on the notion that competition is not only global but also symmetric.[14] Indeed, sales and profits depend only on the distribution of rival prices and not on the identities or locations of the firms that post those prices.

A number of models of differentiated products lie somewhere in between these two extremes. For example, with the characteristics approach to demand (Lancaster 1966, Baumol 1967, and Gorman 1980) products compete along several dimensions. Moreover, as the number of dimensions increases, so does the number of neighbors.[15]

[13]This assumes that there is no mill–price undercutting (see Eaton and Lipsey 1976).

[14]We use the term global competition to describe a situation where all cross–price elasticities are positive but need not be equal. With local competition, in contrast, most cross–price elasticities are zero *a priori.*

[15]For example, Archibald and Rosenbluth (1975) show that when the dimension of the characteristic space is three, firms have on average six neighbors. With four or more dimenions, however, the number of neighbors depends only on the number of firms and is independent of the dimension of

Researchers have also investigated classes of preferences that give rise to the two extremes as special cases (e.g. the rank–ordering model of Deneckere and Rothschild (1992) and the symmetric/circle model of Anderson and de Palma (2000)).

When evaluating a merger, it is important to locate the industry on the global/local spectrum. Indeed, markets where competition is global tend to be more competitive than markets where rivalry is local. This is true because, in a global market, all products compete with all others, whereas in a local market, firms have protected market niches. Moreover, when competition is symmetric, the identities of the merging firms are unimportant and only their market shares matter. With local competition, in contrast, the characteristics of the products that each firm produces are crucial in determining the effect of the merger on prices.

3.2 Empirical Models of Differentiated Products

When products are homogenous, only total supply matters, and a single price prevails in the market. There is therefore only one price elasticity of demand to estimate. When products are differentiated, in contrast, the situation is more complex from an econometric point of view. Indeed, suppose that there are n brands of a differentiated products where n is large. The data, however, consist of a single cross section or a short panel. In order to estimate the n^2 cross–price elasticities, considerable structure must be imposed on the problem. The choice of structure to impose differentiates the various studies.

Most empirical studies of markets in which products are differentiated are cast in a discrete–choice framework. This means that individuals purchase at most one unit of their most preferred brand.[16] Within this framework, there are two commonly used classes of models: a global random–utility model in which each product competes with every other, albeit with varying intensity, and a local spatial model in which most cross–price elasticities are assumed to be zero.

A typical random–utility model makes use of a utility function that is linear in product characteristics, product price, and an ideosyncratic term that is often assumed to have an extreme–value distribution. Aggregation of individual demands is accomplished by integrating over this distribution. If individual draws from the distribution are independent and identically distributed, one has a multinomial logit, which places severe restrictions on substitution possibilities. Indeed, the i.i.d. assumption imposes symmetry *a priori*. If, in contrast, consumer tastes are allowed to be correlated across products in a restricted fashion that involves *a priori* product groupings, one has a nested multinomial logit (NML) that is somewhat more flexible. Finally, if the coefficients of the product–characteristic variables are allowed to vary more generally, one has a random–coefficients model that allows for quite general

the characteristic space.

[16] A large fraction of the empirical papers deals with the automobile market (e.g. Bresnahan 1981 and 1987, Berry, Levinsohn, and Pakes 1995, Feenstra and Levinsohn 1995, Goldberg 1995, Verboven 1996, Fershtman and Gandal 1998, and Petrin 1998), where this assumption is reasonable.

patterns of substitution.[17]

Highly localized spatial models are less common than random–utility models, and we discuss only two. Bresnahan (1981 and 1987) estimates a model of vertical product differentiation with a single parameter that captures quality differences. With his model, products compete directly only with their two nearest neighbors, one of higher and the other of lower quality. Feenstra and Levinsohn (1995), in contrast, allow for multiple dimensions of diversity and compute endogenous market boundaries in this larger space. They do this by assuming that the transport–cost (or utility–loss) function is quadratic in m–dimensional Euclidean space, where m is the number of characteristics. With both models, products that do not share a market boundary do not compete directly (i.e., their cross–price elasticities are zero).

Empirical models that allow for variety in consumption of a non–random sort are less common in the differentiated–products literature. A recent study by Hausman, Leonard, and Zona (1995), however, is based on the notion that consumers can, and often do, purchase several varieties or brands. These authors consider a multi–stage budgeting problem, where consumers first decide how much of the product (beer) to consume, then decide which product types to purchase (e.g. premium, regular, or light), and finally select individual brands. The structure of their model, which involves *a priori* product groups, is thus similar to a NML. Substitution possibilities within groups, however, are more flexible than with a NML, but the number of brands that can be included in each group is smaller.

Empirical models of differentiated products have been used to assess many practical economic issues, including the effects of mergers. For example, Werden and Froeb (1994) use a logit demand model to evaluate mergers among US long–distance carriers, Hausman, Leonard and Zona (1994) use an 'almost ideal demand system' to evaluate mergers in the US brewing industry, and Nevo (1997a) uses a random–coefficients model to evaluate mergers in the US ready–to–eat breakfast–cereal industry. .

In the next sections we develop a model in which individuals, who have a taste for diversity, purchase variable amounts of one or more brands of a differentiated product. We make no distributional assumptions; instead, we impose the conditions that are required for exact aggregation, and we model unobserved heterogeneity nonparametrically. Our method can handle endogenous prices and measurement error in a straight–forward fashion through the use of instrumental variables. Furthermore, our framework nests global and local models. Nesting is accomplished through the use of several notions of distance, or its inverse closeness. Some of those measures allow the strength of competition to decay gradually with distance and are thus global, whereas others are discrete or local.

[17]Examples of the use of a NML include Goldberg (1995), Verboven (1996), and Fershtman and Gandal (1998). Bresnahan, Stern, and Trajtenberg (1997) estimate a generalized extreme value model that is not hierarchical. Finally, Berry, Levinsohn, and Pakes (1995), Nevo (1997a and b), Davis (1997), and Petrin (1998) estimate random–coefficients models. For a more comprehensive discussion of these models, see Berry (1994).

4 The Beer Brands Model

In Pinkse, Slade, and Brett (1998), we develop an empirical method that can be used to locate real–world markets on the global/local spectrum. We consider the case where buyers are downstream firms and start with the their individual demands. We then aggregate their choices into upstream–firm demands for each product. Here, we extend that model to encompass buyers that are individuals. The principal difference is that, whereas there are no restrictions that must be satisfied for consistent aggregation of competitive profit functions, consistent aggregation of utility functions requires additional assumptions.

We consider a situation where heterogeneous individuals consume varying amounts of the brands of a differentiated product. In addition, it is possible that some individuals consume no brand of this product. All other commodities are aggregated into an outside good that all individuals consume. The market for the differentiated product is assumed to be imperfectly competitive, whereas the outside good is competitively supplied. In what follows, the demand and cost sides of the market are described and equilibria of pricing games are discussed.

4.1 Demand

Suppose that there are n brands of a differentiated product, each of which is produced by one of K firms.[18] No two brands are identical. Let $\tilde{p}_i$ be the nominal price of the ith brand, $i = 1, \ldots, n$. There is also an outside good that is sold at a nominal price p_0.

The hth individual consumes a vector $q_h = (q_{1h}, \ldots, q_{nh})^T$ of the differentiated product, with $q_{ih} \geq 0, i = 1, \ldots, n$, and q_{0h} of the outside good, with $q_{0h} > 0, h = 1, \ldots, H$. Furthermore, this individual has nominal income $\tilde{y}_H$ and indirect–utility function $\tilde{u}_h(p_0, \tilde{p}, \tilde{y}_h)$, where $\tilde{p} = (\tilde{p}_1, \ldots, \tilde{p}_n)^T$. By Roy's theorem, individual demands for the differentiated product are

$$q_{ih} = \frac{\partial \tilde{u}_h / \partial \tilde{p}_i}{-\partial \tilde{u}_h / \partial \tilde{y}_h}. \tag{1}$$

Not knowing the functional form of $\tilde{u}_h$, we approximate it with a flexible functional form. We choose a normalized quadratic (Berndt, Fuss, and Waverman 1977 and McFadden 1978), where prices and incomes are normalized or divided by p_0. Specifically, $\tilde{u}_h(p_0, \tilde{p}, \tilde{y}_h) \approx p_0 u_h(1, p, y_h)$, where $p = p_0^{-1}\tilde{p}, y_h = p_0^{-1}\tilde{y}_h$,

$$u_h(1, p, y_h) = -\left[a_{0h} + a_h^T p - p_0 y_h(\gamma_0 + \gamma^T p) + \frac{p_0}{2}\; p^T B_h p\right], \tag{2}$$

and each B_h is an arbitrary $n \times n$ symmetric, negative–semidefinite matrix.

Equation (2) is flexible in prices. In other words, it places no restrictions on the matrix of elasticities of substitution between brands of the differentiated product. Moreover, each individual occupies a different location in taste space and thus has a

[18]Firms can produce more than one brand, but no brand is produced by more than one firm.

different set of substitution patterns. Finally, the utility function is in Gorman polar form and can therefore be aggregated to obtain brand–level demands.[19]

Using (1) and (2), individual demands are

$$q_{ih} = \frac{a_{ih} + \sum_j b_{ijh} p_j - \gamma_i y_h}{p_0(\gamma_0 + \gamma^T p)}. \tag{3}$$

In equation (3), $p_0(\gamma_0 + \gamma^T p) = \gamma_0 p_0 + \gamma^T \tilde{p}$ is a price index that can, without loss of generality, be set equal to one in a cross section or very short time series. After this normalization, aggregate product demands become

$$q_i = \sum_h a_{ih} + \sum_j \left(\sum_h b_{ijh} \right) p_j - \gamma_i \left(\sum_h y_h \right) = a_i + \sum_j b_{ij} p_j - \gamma_i y, \tag{4}$$

where $a_i = \sum_h a_{ih}, b_{ij} = \sum_h b_{ijh}$, and $y = \sum_h y_h$ is aggregate income.

Unfortunately, it is not possible to estimate the parameters of (4) from a single cross section or short panel of n brands.[20] It is therefore necessary to place some structure on the parameters, which we do as follows. Following Pinkse, Slade, and Brett (1998), we assume that a_i, which determines the size of brand i's market, and b_{ii}, which determines the own–price elasticity, depend on brand and regional characteristics and time–period dummies.[21] For example, when the product is beer, the product characteristics might be the brand's alcohol content, product type (e.g. lager, ale, or stout), and brewer identity, whereas regional characteristics might be population, per capita income, and unemployment rate.

$b_{ij}, j \neq i$, in contrast, which determines substitutability between products i and j, is assumed to depend on a set of measures of distance (or its inverse closeness), d_{ij}, between the two products in some set of metrics. For example, when the product is beer, the measures of closeness might be market–share proximity, alcohol–content proximity, and dummy variables that indicate whether the brands are brewed by the same brewer and whether they belong to the same product type (e.g. whether both are lagers). In addition, one can construct distance indicators that have been used by others, such as the common–market–boundary measure of Feenstra and Levinsohn (1995), that depend on the prices and locations of all brands. Although restrictive, these assumptions on the parameters of the aggregate–demand functions are consistent with uncoordinated choices of heterogeneous utility–maximizing individuals.

Let $X = (x_{im}), m = 1, \ldots, M$, be a matrix of observed brand, regional, and time–period variables. If in addition there are unobserved brand and regional characteristics, u, (4) can be written in matrix notation as

$$q = \alpha + X\beta + Bp + u, \tag{5}$$

[19]See Gorman (1953, 1961) or Blackorby, Primont, and Russell (1978) for a discussion of the conditions that are required for consistent aggregation across households.

[20]The matrix $B = [b_{ij}]$ alone has $n(n+1)/2$ parameters.

[21]Regions of the country have not been mentioned. One can model different regions by assuming that each brand/region pair is a different product with zero cross–price elasticities across regions.

where α is a vector of intercepts that we treat as random effects, and β is a vector of parameters that must be estimated.

The matrix $B = (b_{ij})$ has two parts: b_{ii} is a parametric function of $X_i = (x_{i1}, x_{i2}, \ldots, x_{iM})^T$, and $b_{ij} = g(d_{ij})$, $i \neq j$, is a function of the measures of distance between brands i and j. As we are interested in placing as little structure as possible on substitution patterns, we estimate $g(.)$ by semiparametric methods.

Finally, The random variable u, which captures the influence of unobserved product and regional variables, can be heteroskedastic and correlated across observations. We assume, however, that the unobserved characteristics, u, are mean independent of the observed characteristics, X. Whereas this assumption is problematic, it is standard in the literature.[22] Moreover, it can be tested.

4.2 Marginal Costs

A good approximation to demand is necessary but not sufficient for our equilibrium calculations. In addition, we need estimates of marginal costs. There are two common methods of estimating marginal costs econometrically. With the first, researchers assume that a particular game is being played (e.g. Bertrand–Nash) and write down the first–order conditions for that game. Those conditions typically include marginal–cost variables. One can therefore estimate the first–order condition along with the demand equation and use the estimated equations to infer marginal costs[23] This method is efficient if the firms are indeed playing the assumed game. If they are playing a different game, however, the estimates of marginal cost so obtained are biased.

The second method involves estimating marginal costs from first–order conditions that also involve a vector of parameters Θ, which are often called market–conduct parameters. These parameters summarize the outcome of the game that the firms are playing without specifying that game. In other words, the econometrician takes an agnostic position and lets the data determine if the observed market outcome is indistinguishable from the equilibrium of a particular static game. No attempt is made to model the actual game, however, or to determine the reasons why players might deviate from static equilibrium. This literature, which is summarized in Bresnahan (1989), has recently been criticized. Indeed, the interpretation, and therefore the usefulness, of the market–conduct parameters that have been estimated using standard techniques has been questioned by Corts (1999). He points to problems with the identification of the market–conduct parameters that can lead to biased estimates, especially when deviations from static equilibrium are large.[24]

[22]For a discussion of the difficulties involved in relaxing this assumption, see Berry (1994).

[23]See, for example, Berry (1994), Berry, Levinsohn, and Pakes (1995), and Petrin (1999).

[24]Genesove and Mullin (1998) use engineering data on marginal costs, which they compare to marginal–cost estimates obtained in the above manner. They find that the bias is small in their application. However, the outcomes for their industry (sugar) were close to $\Theta = 0$, a situation in which the bias is predicted to be small.

We do not use either of the econometric techniques to obtain our marginal costs. Instead we make use of a detailed engineering study of beer–production costs by product type that was performed by the Monopolies and Mergers Commission (1989).[25] We update the MMC estimates to reflect inflationary trends, and we use the updated costs, together with our estimated demand equation, to solve for market–conduct parameters analytically. In so doing, we avoid the difficulties that are inherent in the more standard techniques.

4.3 Pricing Games

The estimated demands and costs can be used to evaluate the brewers' game. We begin by considering a static pricing game and then discuss how we can test the Bertrand assumption.

4.3.1 The Static Game

Suppose that player $k, k = 1, \ldots, K$, controls a set of prices p_i with $i \in \tilde{k}$, where $\kappa = [\tilde{1}, \tilde{2}, \ldots, \tilde{K}]$ is a partition of the integers $1, \ldots, n$. Let $-\tilde{k}$ be the set of integers that are not in $\tilde{k}$, $p_{\tilde{k}}$ be the set of prices that k controls, and $p_{-\tilde{k}}$ be the set that k does not control. For given κ, player k seeks to

$$\max_{p_{\tilde{k}}} \ \pi_k(p, \kappa) = \sum_{j \in \tilde{k}} \Big\{ (p_j - c_j)(A_j + \sum_{m=1}^{n} b_{jm} p_m) \Big\} - f_k, \tag{6}$$

where, in the notation of equation (5), $A_j = \alpha_j + \beta^T X_j, c_j$ is the marginal cost of producing brand j, and f_k is firm k's fixed cost.

The n first–order conditions for this game are linear in the unknown price vector, p. In theory, one can solve the game by simply solving those equations, a procedure that involves only matrix inversion. In practice, however, a solution obtained in this manner can violate the constraints, $p_i \geq 0$, $q_i \geq 0$, $i = 1, \ldots, n$. When violations occur, one must compute constrained equilibria.[26]

To solve the constrained game, we use a technique that is developed in Slade (1994). In that paper, necessary and sufficient conditions are derived that, when satisfied by individual payoff functions, $\pi_k(.,.)$, imply that the game is observationally equivalent to a single–agent maximization problem.[27] Since maximization problems are easier to solve than equilibrium problems, especially when constraints are involved, games that satisfy those conditions are easier to work with.

[25]Exogenous cost information is also used by, e.g., Genesove and Mullin (1998), Nevo (1997b), and Wolfram (1999).

[26]It is standard in the literature to either approximate the solution to the post–merger game using pre–merger market shares (e.g. Hausman, Leonard, and Zona 1994 and Werden and Froeb 1994) or to solve the unconstrained problem (e.g. Nevo 1997a).

[27]By observationally equivalent, we mean that it has the same first–order conditions.

When the appropriate conditions are satisfied, we call the function that the oligopolistic market 'maximizes' a fictitious–objective function.[28] It is straightforward to show that such a function exists if and only if the individual profit functions can be written as[29]

$$\pi_k(p,\kappa) = F(p,\kappa) + \Gamma_k(p_{-\tilde{k}},\kappa). \tag{7}$$

Moreover, the fictitious–objective function is $F(p,\kappa)$.

With the profit functions (6), a fictitious–objective function exists if and only if $b_{ij} = b_{ji}$ for all i and j, a condition that is also required by the theory (i.e., if the demands come from a utility function). With our problem, B is symmetric if all of the distance measures are symmetric, a requirement that can be fulfilled by construction. When B is symmetric, the fictitious-objective function corresponding to profit functions (6) is

$$\begin{aligned} F(p,\kappa) &= \sum_{j=1}^{n}\Big[A_j + b_{jj}(p_j - c_j)\Big]p_j \\ &+ \sum_{k=1}^{K}\Big\{\sum_{j\in\tilde{k}}\Big[\sum_{r\in\tilde{k},r>j} b_{jr}(2p_jp_r - c_rp_j - c_jp_r)\Big]\Big\} \\ &+ \sum_{k=1}^{K}\Big\{\sum_{j\in\tilde{k}}\Big[\sum_{m\in-\tilde{k},m>j} b_{jm}p_jp_m\Big]\Big\}. \end{aligned} \tag{8}$$

With this game, a merger (divestiture) involves changing K, the number of players, and κ, the partition of the integers. For any partition, the appropriate $F(.,.)$ can be found, and it can be maximized subject to the nonnegativity constraints.

4.3.2 Testing the Bertrand Assumption

The approach just described is valid as long as the firms in the market are engaged in a static pricing (Bertrand) game. There are a number of reasons, however, why this might not be the case. Complexities arise for at least two reasons: the game is repeated, and it is played by agents, not principals. Dynamic strategic and/or agency considerations might therefore surface.[30]

[28] Such a function has also been called a 'potential' function (see Monderer and Shapley 1996).

[29] This is an obvious generalization of the result in Slade (1994) to the case where each player controls more than one variable.

[30] When firms are engaged in a supergame, we know from the famous folk theorem of repeated games that any individually rational outcome can be sustained as a subgame–perfect equilibrium of that game. In addition, except in the case of managed public houses, which are owned by the brewer and operated by an employee of the brewer, publicans (retailers) set retail prices, whereas brewers (manufacturers) set wholesale prices. When a game is played by agents, principals have a motive for distorting their agents' incentives. See, for example, Fershtman and Judd (1987), where

If the equilibrium assumption is incorrect, the model's predictions will be biased. It is therefore important to assess our equilibrium–solution concept. To do this, we estimate market–conduct parameters, one for each brand, where a market–conduct parameter adjusts the Lerner index or price/cost margin to allow for rival responses.[31]

Equation (6) expresses firm k's objective function. A fairly general first–order condition for the choice of p_i by k, with i in $\tilde{k}$ can be written as

$$\begin{aligned} A_i &+ \sum_{j \in \tilde{k}} [(b_{ij} + b_{ji}) p_j - b_{ji} c_j] + \sum_{m \in -\tilde{k}} b_{im} p_m \\ &+ \sum_{j \in \tilde{k}} \left\{ (p_j - c_j) \left[\sum_{m \in -\tilde{k}} \Theta_{mi} b_{jm} \right] \right\} = 0, \qquad i = 1, \dots, n. \qquad (9) \end{aligned}$$

The Bertrand–Nash equilibrium is obtained by setting $\Theta_{mi} = 0$ for all m and i and solving for p.

There are n first–order conditions of the form of (9), but there can be as many as $n(n-1)$ Θ's. For tractability, we assume that $\Theta_{mi} = \theta_i$ for all m in $-\tilde{k}$. In other words, we assume that there is one market–conduct parameter per brand.

Equation (9) with $\Theta_{mi} = \theta_i$ can be used to test our equilibrium assumption. Specifically, given price and cost vectors, p and c, one can solve for the vector of market–conduct parameters, $\hat{\theta}$. Since the estimates, $\hat{\theta}_i, i = \dots, n$, are random variables, one can test if they are, on average, zero.

5 Estimation and Testing

5.1 Estimation

Our semiparametric estimator is described in detail in Pinkse, Slade, and Brett (1998) and is therefore discussed only briefly here. Additional details can be found in appendix A. Our estimating equation is the demand function (5). This equation contains a vector, d, of measures of distance between brands in different metrics. Specifically, we have assumed that the off–diagonal elements of the matrix $B, b_{ij}, i \neq j$, which determine the cross–price elasticities, are a common function $g(.)$ of the distance measures, d_{ij}. The elements of d must be specified by the econometrician; the functional form of g, however, is determined by the data.

delegation leads to more aggresive behavior, and Bonnano and Vickers (1988) and Rey and Stiglitz (1995), where it leads to less. Slade (1998) assesses the game that is played by agents in the UK beer industry.

[31] The term 'conjecture' is often used instead of market conduct because the parameters are often interpreted as conjectured responses, $\Theta_{ji} = \partial p_j / \partial p_i, j \in -\tilde{k}$. This interpretation, however, is not useful in a situation where nonzero parameters can arise for so many reasons. Nevertheless, the first–order conditions are obtained by allowing these partial derivatives to be non–zero.

(5) can be rewritten as

$$q_{irt} = b_{iirt}p_{irt} + \sum_{j\neq i} g(d_{ijrt})p_{jrt} + \beta^T X_{irt} + u_{irt},$$
$$i = 1, \ldots, n, \quad r = 1, \ldots, R, \quad t = 1, \ldots, T, \tag{10}$$

where the intercepts have been included in X,[32] n is the number of brands, R is the number of regions, and T is the number of time periods.

We use a series expansion to approximate g and, as is standard, allow the number of expansion terms that are estimated to increase with the sample size. There are three concerns that must be dealt with in deriving our estimator. First, the right–hand–side variables contain rival prices that are apt to be correlated with u, second, in addition to the error term u, there is an approximation error that is due to neglected expansion terms, and third, the number of instruments must grow as the number of expansion terms increases.

We deal with endogeneity by taking an instrumental–variables (IV) approach. Our concern here is with the choice of instruments. In particular, we need instruments that vary by brand. The exogenous demand and cost variables, X and c, are obvious choices, and some of those variables vary by brand. A number of other possible choices of instruments have been discussed in the differentiated–products literature. For example, Baker and Bresnahan (1985) suggest using individual–brand cost shifters. Unfortunately, however, brand–specific cost variables are hard to find. Hausman, Leonard, and Zona (1994), in contrast, assume that systematic cost factors are common across regions and that short–run shocks to demand are not correlated with those costs. This allows them to use prices in one city as instruments for prices in another. Finally, Berry, Levinsohn, and Pakes (1995) point out that, since a given product's price is affected by variations in the characteristics of competing products, one can use rival–product characteristics as instruments.

The identifying assumptions that we make involve a combination of the second and third suggestions. Specifically, we assume that prices in region one are valid instruments for prices in region two and vice versa. In addition to the above argument for the weak exogeneity of these instruments, the brands of beer that are sold in one region are not substitutes for those that are sold in another. Profit–maximizing decision makers will therefore not coordinate their price choices across regions. Furthermore, in the majority of establishments (85%), prices are chosen by the retailer (the publican) and not by the manufacturer (the brewer).

We also use rival characteristics to form instruments by multiplying the vectors of characteristics by weighting matrices W, where each W is an element of d. To illustrate, suppose that W^1 is the same–product–type matrix (i.e., the matrix whose i, j element is one if brands i and j are the same type of product — both stouts for example — and zero otherwise) and that x^1 is the vector of alcohol contents of the brands. The product, W^1x^1, has as ith element the average alcohol content of rival brands that are of the same type as i.[33] We are thus able to create additional

[32] The random parts of the intercepts have been included in u.

[33] The weighting matrices are normalized so that the rows sum to one.

instruments, and our model is overidentified.

Finally, we create additional instruments when the number of expansion terms grows by applying the same functions to the instruments as to the distance measures. For example, if the series approximation involves polynomials, we take powers of the instruments as well as of the distance measures.

In Pinkse, Slade, and Brett (1998) we suggest a semiparametric estimator for g and β that is based on the traditional parametric IV estimator. Furthermore, we demonstrate that g and β are identified and that our estimator is consistent, and we derive the limiting distributions of $\hat{\beta}$ and $\hat{g}$. Finally, we show how their covariance matrix can be estimated. Our covariance–matrix estimator is similar to the one that is proposed in Newey and West (1987) in a time–series context. In particular, observations that are close to one another are assumed to have nonzero covariances, where closeness is measured by one of the distance metrics. Our estimator, however, which involves correlation in space rather than time, can be used when the errors are nonstationary, as is more apt to be the case in a spatial context.

5.2 Tests of Instrument Validity

We have assumed that our instruments are valid (i.e., that they are uncorrelated with the errors in our estimating equation). The exogeneity of some of our instruments, however, in particular price in the other region, is questionable. Furthermore, many other instruments are created from this variable and thus might also be suspect. We therefore employ a formal test of exogeneity, one that is valid in the presence of heteroskedasticity and spatial correlation of an unknown form.

Suppose that the estimating equation is $y = R\gamma + u$ and that $\{(z_i, u_i, Q_i, R_i)\}$ is i.i.d., where z_i is the suspect instrument, Q_i is the set of nonsuspect instruments, R_i is the set of explanatory variables, which includes at least one endogenous regressor, and u_i is the error for observation i. For z to be a valid instrument, u and z must be element–wise uncorrelated, i.e. $E(z_i u_i) = 0$. Let $P_Q = Q(Q^T Q)^{-1} Q^T$, $\Omega = Var(u|R, z, Q)$, $M = I - R(R^T P_Q R)^{-1} R^T P_Q$, $\tilde{V} = z^T M \tilde{\Omega} M z$, where $\tilde{\Omega}$ is our estimate of Ω, and $\hat{u}$ be the residuals from an IV estimatation using Q (but not z) as instruments. Then, under mild regularity conditions on $\tilde{\Omega}$,

$$\tilde{V}^{-1/2} z^T \hat{u} = \tilde{V}^{-1/2} z^T M u \tag{11}$$

has a limiting $N(0, 1)$ distribution (see Pinkse, Slade and Brett (1998)).

If one wants to test more than one instrument at a time, it is possible to use a matrix Z instead of the vector z to get a limiting $N(0, I)$ distribution. Taking the squared length, one has a limiting χ^2–distribution whose number of degrees of freedom is equal to the number of instruments tested.

6 Data and Preliminary Data Analysis

6.1 Demand Data

Most of the data were collected by StatsMR, a subsidiary of A.C. Nielsen Company. An observation is a brand of beer sold in a type of establishment, region of the country, and time period. Brands are included in the sample if they accounted for at least one half of one percent of one of the markets. There are 63 brands. Two bimonthly time periods are considered, Aug/Sept and Oct/Nov 1995, two regions of the country, London and Anglia, and two types of establishments, multiples and independents. There are therefore potentially 504 observations. Some brands, however, were not sold in a particular region, time period, and type of establishment. When this occurred the corresponding observation was dropped in both regions of the country.[34] This procedure reduced the sample to 444 observations.

Establishments are divided into two types. Multiples are public houses that either belong to an organization (a brewer or a chain) that operates 50 or more public houses or to estates with less than 50 houses that are operated by a brewer. Most of these houses operate under exclusive–purchasing agreements (ties) that limit sales to the brands of their affiliated brewer.[35] Independents, in contrast, can be public houses that are not owned by a brewer or chain, clubs,[36] or bars in hotels, theaters, cinemas, or restaurants. Independent establishments are usually not tied to a brewer.

For each observation, we have price, sales volume, and coverage. Price, which is measured in pence per pint, is the average for that brand, type of establishment, region, and time period. This variable is denoted PRICE. Volume, which is measured in 100 barrels, is total sales of the brand in the region, time period, and type of establishment. This variable is denoted VOL. Finally, coverage, which is the percentage of outlets in the region and type of establishment that stocked the brand at the beginning of the time period, is denoted COV.

In addition, we have data that vary by brand but not by region, establishment type, or time period. Those variables are alcohol content, product type, and brewer identity.

Each brand has an alcohol content that is measured in percentage. This continuous variable is denoted ALC. Moreover, brands whose alcohol contents are greater than 4.2% are called premium, whereas those with lower alcohol contents are called regular beers. We therefore created a dichotomous alcohol–content variable PREM that equals one for premium brands and zero otherwise.

Brands are classified into four product types, lagers, stouts, keg ales, and real ales. Two types of ales are distinguished because real or cask–conditioned ales undergo a second fermentation in the cask, whereas keg ales are sterilized. Unfortunately, three

[34] Dropping an observation in both regions of the country is necessary because we use prices in one region as instruments for prices in the other.

[35] Many tied houses also sell brands that are brewed by firms that do not have tied estates (e.g. Guiness) as well as a 'guest' cask–conditioned ale.

[36] A club is an organization where consumption of liquor is restricted to members and their guests.

brands — Tetley, Boddingtons, and John Smiths — have both cask and keg–delivered variants. Since it is not possible to obtain separate data on the two variants of these brands, we adopt the classification that is used by StatsMR. Dummy variables that distinguish the four product types are denoted $\mathrm{PROD}_i,\ i = 1, \ldots, 4$.

There are ten brewers in the sample, the four nationals, Bass, Carlsberg–Tetley, Scottish Courage, and Whitbread, two brewers without tied estate, Guiness and Anheuser Busch, and four regional brewers, Charles Wells, Greene King, Ruddles, and Youngs. Brewers are distinguished by dummy variables, $\mathrm{BREW}_i,\ i = 1, \ldots, 10$.

We created dummy variables that distinguish the establishment types, PUBM and PUBI for multiples and independents, regions of the country REGL and REGA, for London and Anglia, and time periods, PER1 and PER2.

We also created a number of interaction variables, which are denoted PRXXX, where XXX is a characteristic. For example, PRALC_i is $\mathrm{PRICE}_i \times \mathrm{ALC}_i$.

Finally, as a straw man, we created an average–rival–price variable, RPSHARE, which is a market–share–weighted average of the prices of each brand's rivals. This is the most symmetric measure of rivalry that we use. Indeed, it has something in common with a logit–demand system, since it implies that only the distribution of prices matters and not the identities of the brands that post those prices. Furthermore, it implies that market shares alone determine substitution possibilities.

The set of endogenous variables consists of all variables that are constructed from prices or volumes. Coverage, in contrast, is considered to be weakly exogenous.[37] Whereas coverage would be endogenous in a longer-run model, according to people in the industry, there is considerable inertia in brand offerings. This is partially due to the existence of contracts between wholesalers and retailers and partially due to the need to change taps when brands are changed.[38] Finally, coverage is defined as the fraction of establishments that offered the brand at the beginning of the bimonthly period and does not change during that period.

6.2 Preliminary Data Analysis

Table 4 shows summary statistics by product type. 4A divides observations into the three major product groups: lagers, stouts, and ales, whereas 4B gives statistics for the two types of ales. In these tables, total volume is the sum of sales for that product type, whereas average volume is average sales per establishment. 4A shows that, on average, stouts are more expensive than lagers, which are more expensive than ales, and that lagers have the highest alcohol contents, followed by stouts and then ales. In addition, average coverage is highest for stouts. This statistic, however, is somewhat misleading, since it is due to the fact that Guiness is an outlier that is carried by a very large fraction of establishments. Finally, cask–conditioned ales have higher prices and sell larger volumes than keg ales. However, the volume statistics must be viewed with caution, since some of the most popular brands have keg variants.

[37] This assumption is tested below.

[38] The guest beer is an exception. With such beers, a sign with the name of the brand is merely hung over the tap.

Table 5 contains summary statistics by establishment type and region of the country. This table shows that prices are higher and volumes are lower in multiple establishments. In addition, both prices and volumes are higher in London.

6.3 Marginal Costs

The Monopolies and Mergers Commission performed a detailed study of brewing and wholesaling costs by brand. In addition, they assessed retailing costs in managed public houses.[39] A summary of the results of this study is published in MMC (1989). Although the assessment of costs was conducted on a brand basis, only aggregate costs by product type are publicly available. The MMC used volume weights to calculate average unit costs, where the volumes were based on the sales of each brand in managed houses.

Brewing and wholesaling costs include material, delivery, excise, and advertising and marketing expenses per unit sold. Retailing costs include labor and wastage, and combined costs include VAT.[40] If brewing were subject to constant returns to scale, these would be marginal costs. Under increasing returns, however, unit costs overestimate marginal costs. Unfortunately, we have no quantitative information on economies of scale and therefore use the MMC unit–cost figures.

We updated the MMC cost figures to reflect inflation. To do this, we collected the closest available price index for each category of expense. We then multiplied each cost category by the ratio of the appropriate price index in 1995 to the corresponding index in 1985.

6.4 The Metrics

To implement the estimation, we must specify the elements of the distance vector d. We experimented with a number of notions of distance or its inverse, closeness: beers that are of the same product type, are brewed by the same brewer, have similar coverages, and have similar alcohol contents. Furthermore, we considered beers that are nearest neighbors or share a market boundary in alcohol/coverage space. We discuss each metric in turn.

Table 4 shows that each of the four product types has a unique set of characteristics. It is reasonable to assume, therefore, that many customers who drink stout, for example, and do not find their favorite brand are apt to choose another brand of stout as a substitute. Our first measure of closeness, which we denote WPROD, has i, j element equal to one if beers i and j are the same type of product and zero otherwise.

Normally, one would not expect brewer identity to play a large role in determining substitution patterns. The UK system of tied houses, however, that involves brewer

[39] Managed public houses are owned and operated by the brewer.

[40] See Slade (2000) for more details about brewing and retailing costs.

exclusivity agreements, could cause beers that are brewed by the same firm to substitute for one another.[41] Our second measure of closeness, which we denote WBREW, has i, j element equal to one if beers i and j are brewed by the same firm.

The above measures are discrete or local. We also consider two continuous or global measures of closeness. The first of these captures closeness in coverage space. Specifically, $\text{WCOV}_{ij} = 1/[1 + |\log(\text{COV}_i) - \log(\text{COV}_j)|]$.[42] We use this measure to test if, for example, popular national brands are substitutes for other popular national brands, whereas specialty brands are substitutes for other specialty brands.

Our second continuous measure captures closeness in alcohol–content space. Specifically, $\text{WALC}_{ij} = 1/(1+2|\text{ALC}_i - \text{ALC}_j|)$. We use this measure to test if, for example, light beers substitute for other light beers, and so forth.

Our two continuous characteristics are also used to construct two–dimensional market areas. These can be defined either exogenously, as a function of Euclidean distance, or endogenously, as a function of prices and 'transport costs'. There are four market configurations for each measure: London/Aug/Sept, London/Oct/Nov, Anglia/Aug/Sept, and Anglia/Oct/Nov.[43] To construct these configurations, we averaged over multiple and independent establishments using volume weights.

First, consider the nearest–neighbor measures. The elements of the first matrix, denoted WNNX, where X stands for exogenous, are dummy variables that equal one if beer i is beer j's nearest neighbor and vice versa, 1/2 if i is j's nearest neighbor or j is i's nearest neighbor but not vice versa, and zero otherwise. In performing this calculation, i's nearest neighbor is the beer that is the shortest Euclidean distance from i in alcohol/coverage space.

With the second nearest–neighbor matrix, WNNN, the nearest neighbor is determined endogenously, and the letter N is used to indicate this fact. With this measure, brand i's nearest neighbor has the lowest 'delivered price' at i's location. To find delivered prices, we used a quadratic utility–loss function. Specifically, a consumer located at a point $x = (x_a, x_c)^T$ who purchases a brand located at a point $y = (y_a, y_c)^T$, with subscripts a and c denoting positions on the alcohol and coverage axes, receives a utility loss (or pays a delivered price) equal to $\text{PRICE}_y + b_a(x_a - y_a)^2 + b_c(x_c - y_c)^2$.

To find the utility–loss coefficients, b_a and b_c, we maximized the fit between observed market shares and those predicted using our utility-loss function, where brand i's market area is the set of customers for whom the utility loss associated with i's product is at least as low as the utility loss of any other brand. To perform this calculation, we assumed that consumers are uniformly distributed in alcohol/coverage space, and we normalized so that both alcohol and coverage range between 0 and 1. Normalization implies that a brand's market area and its market share are equal. Finally, we performed a grid search to find the coefficients, $\hat{b}_a$ and $\hat{b}_c$ that yield the

[41] Brands brewed by the same brewer could also be complements, since a high price of one brand could cause customers to avoid the brewer's tied houses altogether.

[42] The functional form of this measure was chosen somewhat arbitrarily. With the nonparametric measures, funcitonal form is irrelevant.

[43] Alcohol content does not vary by market, but coverage does. Moreoever, variation in coverage across regions is substantial.

best fit. Appendix B describes the endogenous calculations in greater detail.

There are also two common–boundary measures, which we denote WCBX and WCBN, for exogenous and endogenous measures, respectively. The elements of the first common–boundary matrix, WCBX, are dummy variables that equal one if i and j share an exogenous–market boundary, but are not nearest neighbors, and zero otherwise, where i's exogenous market consists of the set of consumers who are at least as close in Euclidean distance to i as to any other brand. The boundary between markets i and j thus consists of customers who are equidistant from the two and are not closer to any other brand.

The second common–boundary measure, with associated matrix WCBN, is similar to the first except that market boundaries are endogenous.[44] In other words, with this measure, boundaries are determined by relationships of equality of utility losses, and i's market area consists of those customers for whom the loss associated with i's product is less than or equal to the loses of all other brands. To illustrate, figure 2 depicts endogenous market areas for London in the first time period. Notice that brands are not uniformly distributed in coverage space. In particular, one brand (Guiness) is an outlier with unusually high coverage.

We also constructed variables NCBX (NCBN) to equal the number of exogenous (endogenous) common–boundary neighbors for each brand. On average, brands have 7 common–boundary neighbors.

Matrices corresponding to each discrete metric were normalized so that the elements of each row sum to one. This normalization was performed so that when the price vector is multiplied by a matrix, the ith element of the resulting vector is the average price of, for example, rival beers that are of the same type of product as i. We therefore have measures of the mean of the distribution of rival prices according to each metric as well as the number of competitors over which each mean is taken.

7 The Econometric Estimates

7.1 Parametric Estimates of Demand

Table 6 summarizes the IV estimates of demand. 6A is divided into three sections: the first is the intercept term, a_i, whereas the second is the own–price term, b_{ii}. Both of these are functions of the characteristic vector, X_i. The characteristics in b_{ii}, however, have been interacted with price. The third section is the rival–price term b_{ij}, which is a function of the distance measures, d_{ij}. Variables in this section are weighted averages of rival prices and are denoted RPW, where W is one of the distance matrices. The straw–man variable, RPSHARE, is also included in the third section for comparison purposes.

To conserve on space, the estimated coefficients of the characteristics variables, X, are not shown. Instead, the first row in table 6A indicates their signs, whereas in subsequent rows, their significance is indicated. Furthermore, each equation in this

[44] This measure of closeness is very similar to the one used by Feenstra and Levinsohn (1995).

table contains at most one distance measure. Finally, since brewer fixed effects are never significant, and product-type fixed effects are significant only in specifications in which own and rival-price coefficients are not functions of the characteristics and distance measures, the equations that are shown do not include fixed effects.

In theory, all characteristics that are included in X_i could enter both a_i and b_{ii}. In practice, however, each characteristic is highly correlated with the interaction of that characteristic with price. For this reason, the variables that appear in a_i and those that appear in b_{ii} are never the same. We have tried to allocate the variables in what we think is a sensible fashion. Nevertheless, the allocation is somewhat arbitrary. In addition, since a brand's coverage was found to be an important determinant of both its market size and its own–price elasticity of demand, we have included coverage in both parts of the table. To avoid collinearity, we use different functional forms in the two parts, with LCOV = log(COV) and COVR = 1/COV.

First consider the intercepts, a_i. In all specifications, high coverage is associated with high sales. In addition, sales are higher in independent establishments and in London. Finally, a high alcohol content has a positive but weak effect on sales. None of these results is surprising.

Next consider the own–price effects, b_{ii}. Premium and popular brands have steeper (i.e., more negative) slopes (recall that COVR is an inverse measure of coverage). In addition, when a brand has a large number of neighbors, its sales are more price sensitive.

More important and the focus of the paper are the determinants of brand substitutability. The table shows that the most significant measure of rivalry is RPPROD, which implies that competition is strongest among brands that are of the same product type. In addition, a high share–weighted rival price stimulates sales. The coefficient of RPSHARE, however, is unrealistically large. Indeed, it implies an average total cross-price elasticity of about 100.[45] None of the other measures of substitution is significantly different from 0 at the 5% level.

The equation with the similar–coverage distance measure is very different from the other equations. Indeed, the sizes and significance of the coefficients of the X variables are somewhat aberrant. Furthermore, equations that contain RPCOV are unstable in the sense that minor changes in specification lead to large changes in estimated coefficients.[46] For this reason, further specifications do not include RPCOV.

Table 6B shows a specification with multiple distance measures. As before, the discrete measure same-product-type has the highest explanatory power. In addition beers with similar alcohol contents tend to compete, but this effect is weaker.

Table 6C shows the final parametric specification. Since it is important to have

[45]The poor performance of RPSHARE is probably due to misspecification. In particular, this rival–price measure does not satisfy our mixing condition that requires that dependence decay sufficiently fast with distance. See Pinkse, Slade, and Brett (1998).

[46]Instability seems to be related to the presence of brands with very small market shares. Indeed, the problem disappears when only brands with volumes greater than or equal to 5 are used (75% of the sample). With the smaller sample, the coefficeint of RPCOV is positive and not significant (t stat = 0.5).

precise measures of substitution patterns, and since some of the distance measures are correlated with some of the others, only the same–product–type and similar–alcohol–content measures, RPPROD and RPALC, are included in this specification. This demand equation is thus similar to a nested multinomial logit, where the nests are product types. In addition to the product groupings, however, beers with similar alcohol contents compete, regardless of type. Finally, the standard errors in this equation have been corrected for heteroskedasticity and spatial correlation of an unknown form using our covariance–matrix estimator.

7.2 Nonparametric Estimates of Demand

We have carried out experiments in which g is an unspecified function of the distance between brands in alcohol (and/or coverage) space and several discrete brand–similarity measures. The results are not qualitatively different from the fully parametric case, and hence we present only one specification. This specification is identical to the third equation in table 6A, except that the same–product–type distance measure, WPROD, is interacted with terms of a Fourier–series expansion of difference in alcohol contents (see appendix A).

We report specifications with 3 and 5 expansion terms, which can be found in the bottom portion of table 6A. The standard errors in these equations are corrected for heteroskedasticity and spatial correlation of unknown form, as described in appendix A. The table shows that the semiparametric estimates are identical in sign and similar in significance to the parametric ones. However, since the number of regressors is greater in a semiparametric specification, standard errors tend to be larger.

The estimates of the function g for this specification are shown in figure 3. The graphs show how competition between brands that are of the same product type varies as the difference in their alcohol contents increases. In addition we show 5 and 2.5% asymptotic one–sided pointwise (Bonferroni) confidence bands. These bands have been corrected for spatial correlation, which makes them wider than without such a correction. At a 5% level of significance, we conclude that the cross–price elasticities are nonzero. However, we cannot reject the hypothesis that g is constant at any reasonable level of confidence.

Given that g is an approximately linear function of the distance measures, which means that our IV estimates are consistent, we used the equation that appears in table 6C for the assessment of the model and the analysis of the merger games. First, however, we assessed identification using the test of correlation between the residuals in that equation and various groups of instruments (see subsection 5.2). This process revealed no evidence of endogeneity. For example, when we examined price in the other region by itself, the p–value for the test was 0.20, and when we examined the instruments as a group, the p–value was 0.38.

8 Model Assessment

Prior to evaluating the mergers, we assess the validity of our model of demand, cost, and market equilibrium. We do this in three ways. First, we examine the implied own and cross–price elasticities and compare them to previous elasticity estimates for beer. Second, we test if our equilibrium assumption is consistent with the observed market outcome, and third, we compare observed and predicted equilibrium prices under the ownership structure that prevailed when the data were collected.

8.1 Own and Cross–Price Elasticities

Estimated own–price elasticities for individual brands, which are calculated holding the prices of rival brands constant, vary with the characteristics of the brands. On average, however, they are -5.6, which seems plausible. In particular, our estimates are in line with those obtained by Hausman, Leonard, and Zona (1994), whose own–price elasticities average -5.0. There are few other studies that consider demand at the brand level.

There are, in contrast, many previous estimates of the total price elasticity of demand for beer, which is the percentage change in total beer consumption due to a 1% increase in the prices of all brands. Our estimated total price elasticity is -0.5, which is also in line with previous estimates. For example, Clements and Johnson (1983), Johnson, *et. al.* (1992), Lee and Tremblay (1992), and Hogarty and Elzinga (1972) estimate total own–price elasticities for beer to be -0.1, -0.3, -0.6, and -0.9, respectively.

Partial cross–price elasticities, which are percentage changes in one brand's sales due to a 1% increase in the price of a single rival, vary by brand pair. One can, however, define a total cross-price elasticity, which is the percentage change in one brand's sales due to a 1% increase in the prices of all of its rivals. This elasticity, which varies only by brand, averages 4.1.[47]

As there are many brands, individual partial cross–price elasticities are small. Indeed, since our cross-price elasticities are nonnegative (i.e., the brands are substitutes), stability requires that, on average, their sum be less than the absolute value of the own–price elasticities. In other words, the sum of the elements in a row of the elasticity matrix should, in general, be negative.

It is not practical to examine 63 own and approximately 4,000 cross–price elasticities. Table 7 therefore contains elasticities for a selected subsample of brands. This subsample contains two premium lagers, Lowenbrau and Stella Artois, one regular lager, Tennants Pilsner, two keg ales, Toby and Websters Yorks Bitter, two real ales, and one stout. One of the real ales, Courage Best, is a best–selling brand brewed by a national brewer, whereas the other, Greene King IPA, is a small–sales brand brewed by a regional brewer. Finally, the stout, Guiness, is an outlier with a coverage that is substantially higher than that of any other brand in the sample. In addition to

[47]It is possible to make a rough estimate of average total cross–price elasticities from the numbers shown in the tables in Hausman, Leonard, and Zona (1995). This rough estimate is 3.6.

identifying the type of each brand, the first row of the table shows the brand's alcohol content and the number of its exogenous common–boundary neighbors.

The table shows that there is substantial variation in own-price elasticities. Most of the magnitudes are plausible. Nevertheless, the own-price elasticity of the small-sales brand, Greene King IPA, seems unrealistically high. This is due to the fact that elasticity estimates are inversely related to sales. It seems likely that the model overestimates magnitudes of elasticities for brands with very small market shares. Finally, all of the own-price elasticities in the table are greater than one in magnitude except for Guiness, which has few neighbors in characteristic space.

Turning to the brand cross–price elasticities, the table illustrates that, as expected, these are greater when brands are of the same type and have similar alcohol contents. To illustrate, the three lagers are closer substitutes for one another than for the other brands in the table, and the two premium lagers, Stella and Lowenbrau, are closer substitutes for one another than for the regular lager, Tennants. The table also shows that Guiness is not a close substitute for any of the other brands. In addition, the cross–price elasticities for the small–coverage brand, Greene King IPA, seem high relative to the other estimates, which is a further indication that the model over predicts substitution possibilities for brands with small market shares.

Finally, all of the eigenvalues of the estimated matrix $\hat{B}$, which determines substitution possibilities, are nonnegative. This must be the case if $\hat{B}$ is negative semidefinite and is an indication that the model is well behaved.

8.2 Testing the Equilibrium Assumption

We can use our estimates of demand and cost to test our equilibrium assumption. In particular, we wish to determine if a static game in prices is a reasonable description of interactions in this market. To do this, we estimate market–conduct parameters, one for each brand, and test if they are on average zero.

Figure 4 contains a histogram of the estimated market–conduct parameters, $\{\hat{\theta}_i\}$. These parameters are for London; those for Anglia are similar. There is one very large parameter that corresponds to Guiness ($\hat{\theta}_i = 2.0$), which is not shown in the figure. Due to its extremely high coverage, Guiness is an outlier. For this reason, the discussion that follows excludes Guiness.[48]

The mean $n^{-1}\sum_{i=1}^{n}\hat{\theta}_i$ is 0.006, the standard deviation is 0.115, and the t–statistic for the hypothesis that $n^{-1}\sum_{i=1}^{n}\theta_i = 0$ is 0.57.[49] One cannot reject the hypothesis that, on average, the market–conduct parameters are zero. A static Nash equilibrium in price is therefore not an unreasonable assumption for this market.

[48] We conclude that, whereas the model performs well on average, it predicts less well when brands are in the tails of the market–share or coverage distribution.

[49] The test is based on the fact that any sequence of i.i.d. variates with uniformly bounded moments greater than two, whether they are estimators or not, have a limiting normal distribution; this follows from the Lindeberg theorem, e.g. Doob (1953), theorem 4.2. The notion that the estimators $\hat{\theta}_i$ are independent, even in the limit, is debatable. If they are dependent however, the t–statistics would generally be smaller.

On average, the market–conduct parameters are zero. There are, however, systematic deviations from zero in the estimated θs. In particular, popular and premium brands and brands sold in multiple establishments have larger $\hat{\theta}$s. This means that their observed prices are higher than those predicted by our model of demand, cost, and market equilibrium. The reasons for systematic deviations are beyond the scope of this paper.[50] However, since we are interested in analysing the average response of prices to mergers and divestitures, in subsequent analysis we accept the hypothesis that $\theta = 0$ and solve for static Nash–equlibrium prices under various ownership structures.

8.3 Comparing Observed and Predicted Prices

The *Status Quo* ownership configuration is the situation that prevailed when the data were collected. In other words, with the *Status Quo*, there are ten brewers, four nationals, Bass, Carlsberg–Tetley, Scottish Courage, and Whitbread, two brewers without tied estate, and four regionals.

The first columns of table 8 show observed and Nash–equilibrium prices calculated under the *Status Quo* assumption for London. The average predicted price is 168.4, slightly higher than the observed average of 167.8, and the standard deviation is 29.5, compared to 20.2. *Status Quo* prices are thus approximately centered around the true value but are more variable. Moreover, as with the market-conduct parameters, there are systematic deviations between observed and predicted prices. In particular, the model underpredicts prices of premium products and products sold in multiple establishments.[51] Nevertheless, we feel that, on average, the model predicts well.

9 The Mergers

Our formal analysis of the impacts of mergers and divestitures involves solution of market games under different assumptions about ownership structure. In other words, we compare predicted equilibrium prices. In addition, we examine possible implications for product selection and costs savings more informally.

9.1 Equilibrium Prices

Static NE prices are calculated under three scenarios: *Before*, the *Status Quo*, and *After*. The *Before* scenario is created by undoing the Scottish Courage merger. With

[50] See Slade (1998) for an analysis of why prices in multiple or tied houses are higher than those in independent houses.

[51] The reasons for under prediction of prices are the same as for positive market–conduct parameters. Both indicate that price setting in multiple establishments and of premium brands is less competitive. In particular, the price difference between premium and regular brands is substantially greater than the cost difference.

this scenario, there are five national brewers, and the prices of the brands that belonged to Courage before the merger are chosen by one player, whereas the prices of the brands that belonged to S&N are chosen by another. The *After* scenario is created by allowing the Bass/Carlsberg–Tetley merger to occur. With this scenario, there are three national brewers, and the prices of all Bass and Carlsberg–Tetley brands are chosen by a single player. With all three scenarios, the structure of the rest of the industry is unchanged.

Equilibrium prices under the various scenarios are summarized in table 8. For consistency, *Before* and *After* prices are compared to *Status Quo*, rather than to observed prices. The table shows that undoing the Scottish Courage merger is predicted to have little effect on prices. Indeed, the price decline is less than one percent. A merger between Bass and Carlsberg–Tetley, in contrast, is predicted to result in an overall price increase of 3%. To us, this number seems substantial.

Why is the merger between S&N and Courage not predicted to cause substantial price increases? The answer lies in both the geographic and the brand fit. Geographically, S&N had most of its market in the north, whereas Courage was a southern beer. In London, therefore, Courage dominated S&N, and the local difference in their market shares was greater than the national difference. Moreover, Courage had a strong position in lagers, with best selling Fosters and Kronenbourg. S&N, in contrast, had only Becks, which was not a heavy seller. Comparing ales, both Courage Best and John Smiths were big brands for Courage, whereas S&N's biggest seller, Theakstons, had a much smaller share of the London market. Finally, neither brewer had a best-selling stout.

The brand overlap between Bass and CT, in contrast, was more substantial, particularly in lagers. Indeed, both had top selling lagers, Carling for Bass and Carlsberg for CT, as well as several other popular brands (Tennents for Bass and Castlemaine and Lowenbrau for CT). The overlap in ales was less strong, with only Tetley a very popular brand in London. Geographically, the firms originated in the north (Tetley) or north central (Bass) part of the country.[52] Their geographic strengths were thus more similar than those of Courage and S&N, which meant that their local and national market shares were closer.

The geographic and brand overlap (or lack thereof) is undoubtedly responsible for the different impacts that the mergers are predicted to have on prices. Indeed, the difference in market shares, 37% for Scottish Courage versus 34% for BCT in the geographic and brand market studied, is small. Moreover, if one were to consider local–market shares alone, one would expect the Scottish Courage merger to be more anticompetitive, which is the opposite of what we find.

9.2 Brand Selection

Mergers can affect all aspects of a firm's business, not just prices. In this subsection, we examine the possible ramifications for brand selection informally. Specifically, we compare brand offerings in 1985 to those in 1995.

[52]Carlsberg, of course, originated in Denmark.

Although, in general, there is considerable brand churn, very little of it concerns products than constitute as much as 1/2% of local markets. Moreover, it is clear from interviews with industry managers and marketers that firms are principally interested in the fate of their best-selling brands. None of these disappeared during the ten–year period. Furthermore, according to people in the industry, the brands that did disappear would have done so absent the merger, albeit at a possibly different rate.

In contrast to brand disappearance, new best–selling brands were introduced. These fall into two classes: foreign-owned lagers and hybrid ales. The lagers that are in the sample but were not sold in the UK in 1985 are Grolsch, a Dutch beer that is now brewed by Bass, and Coors, an American beer that is now brewed by Scottish Courage. It is highly unlikely, however, that absent the mergers (or in the case of BCT, had the merger occurred) these brands would not have entered the market.

Hybrid ales are a relatively recent addition to the UK market. A hybrid is a keg ale that uses a nitrogen and carbon dioxide mix in dispensing that causes it to be smoother and to more closely resemble a cask ale. It also has a cloudy appearance when initially dispensed, but the tiny bubbles disappear in a matter of minutes. Caffreys is the most popular hybrid ale. After Bass introduced Caffreys, other brewers followed suit. None of the other brands, however, has been as successful as Caffreys. As with the lagers, it is highly unlikely that the introduction of hybrid ales would have been retarded or aborted by mergers or divestitures.[53]

The two mergers under consideration are thus unlikely to have had much of an impact on product selection. According to industry sources, however, the mergers might have had the effect of concentrating promotional efforts on a smaller number of best–selling brands. If true, the end result could have been less variety in consumption if not in offerings.

9.3 Possible Efficiencies

When a merger occurs it is usually accompanied by restructuring and cost reduction. Indeed, increased efficiency is one of the reasons why firms undertake mergers. It is therefore theoretically possible that cost reductions could have offset market–power increases. If so, the ultimate result could have been no change in prices or even a decline.

The BCT merger, like other mergers in the brewing industry, was expected to result in cost savings of two types: brewery closings and savings in distribution and wholesaling costs through the elimination of duplicate facilities. Retail costs were not supposed to be affected. In the absence of the merger, however, the breweries that were scheduled to close have in fact closed (two that belonged to Bass and three that belonged to CT). In contrast, there has been little reduction in distribution and sales forces. If there are merger-specific offsetting cost savings, we must therefore look for them in a reduction in wholesaling costs, and, according to the MMC's cost estimates, wholesaling costs constitute only 10% of the retail price of beer.

[53]Both Bass and CT brew a hybrid. However, both were introduced before the BCT merger was proposed.

It is possible to assess the issue of whether cost reductions could have offset the forecast increase in market power formally. To do this, we solved for the cost reduction that would be required to insure that, in equilibrium and on average, no price increase would have occured. In performing this exercise, we recognized that only the costs of the merging firms would have been reduced.[54] When we made this calculation, we found that the costs of the merging firms would have to have fallen by just under 20% to offset the increase in market power. Given that wholesaling costs are only 10% of price, and given that only wholesaling costs were expected to fall, a reduction of the required magnitude would not have been possible.

Finally, entry is unlikely to mitigate the effects of mergers. The number of brewers has been in decline for decades, and no firms have entered the national segment of the industry. Indeed, there were six national brewers in 1960, each of which is roughly identifiable with one of the six that existed in 1990, just prior to the Courage/Grand Met merger.

10 Conclusions

Our analysis of brand substitution in UK markets for draft beer indicates that competition is relatively local. In particular, we find that brands that are the of same product type (i.e., both lagers), compete most vigorously. Our model of demand is thus similar to a nested multinomial logit. Competition among groups of products, however, is not a maintained assumption, since this possibility is encompassed in a broader model of substitution. We also find that beers with similar alcohol contents (e.g., two light beers) compete regardless of type, but the strength of this competition is considerably weaker.

When we use our estimated demands and costs to analyse the game that the brewers are playing, we find that a static Nash equilibrium in prices (i.e, a Bertrand game) cannot be rejected. We therefore use the Bertrand assumption to predict the effects of mergers and divestitures, both actual and counterfactual. It is of course possible that changes in ownership structure could cause changes in market conduct. If higher concentration is associated with more collusive outcomes, however, our estimates of price changes due to mergers and divestitures are conservative.

Our analysis of the mergers indicates that, whereas the (consumated) merger between Courage and Scottish & Newcastle had little effect on prices, the proposed merger between Bass and Carlsberg–Tetley would have raised prices by a more substantial amount. This conclusion relies heavily on our findings about the structure of demand. Indeed, the local–market shares of the post–merger firms are not that different from one another, so that, if competition had been symmetric, the effects of the mergers would have been very similar. With localized competition, in contrast, the identity and product mix of each merger partner is key in determining whether

[54] Specifically, we substituted $\tilde{c}_i = (1-\alpha) \times c_i$ if i was a BCT brand, and $\tilde{c}_i = c_i$ if not, into the *After* first–order conditions, and we solved for the value of α that would leave prices unchanged on average.

the merger is anticompetitive.

Finally, our analysis involves only the horizontal–market structure of the beer industry; the complex vertical links that exist are ignored. Indeed, the retail sector in our model is perfectly competitive. Nevertheless, we find that increases in horizontal concentration can lead to increased pricing power. This means that the UK Monopolies and Mergers Commission's emphasis on divestiture of retail outlets in merger cases involving the brewing industry is inadequate and perhaps even counterproductive. For example, if there is market power at the retail level, divestiture could lead to double marginalization and successive output restrictions. With beer retailing, spatial location, the personality of the publican, and the quality of the food and other nonbeer services can endow each establishment with some pricing power. The price changes that are associated with increased horizontal concentration could therefore be exaccerbated by vertical divestiture.[55]

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[55] Slade (1998) concludes that forced divestiture has in fact led to higher prices, holding the horizontal–market structure constant.

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A Semiparametric Estimation

A.1 Outline

The semiparametric estimation method used here is that of Pinkse, Slade and Brett (1998). The method allows the arguments of the function g to be a combination of discrete and continuous measures. The discrete measures can only take finitely many different values and the function g should be continuous in each of the continuous measures, which preferably have a compact support (as we assume is the case here).

Suppose that there are $\mathcal{C}$ permutations of the values of the discrete distance measures. For each category we could allow for a different continuous function of the continuous distance measures. In the semiparametric specification discussed in section 7.2, however, g_{ij} is assumed zero whenever observations i and j correspond to different regions, time periods or product types, which leaves us with just one continuous function to be estimated, say g^*.

The function g^* can be written as an infinite order linear combination of functionals chosen by us and unknown coefficients. We use a Fourier series expansion, meaning that we express g^* (on $[0, 2\pi]$) in terms of the series $1, \cos x, \sin x, \cos(2x), \sin(2x), \ldots$. We cannot estimate all infinitely many unknown coefficients, but limit ourselves (in the application) to the first three or five. The number of expansion terms can be chosen by graphical inspection (which we do) or by an automatic selection method. We did not find much variation in the results across reasonable choices of the number of expansion coefficients estimated. An estimate of g^* can then be constructed as a linear combination of coefficient estimates and the corresponding functionals.

More concretely, the model in (10) can be rewritten as

$$\begin{aligned} q_{irt} &= b_{irt}p_{irt} + n_{\mathcal{G}_{irt}}^{-1} \sum_{j \in \mathcal{G}_{irt}} g^*(d_{ijrt}^C) p_{jrt} + \beta^T x_{irt} + u_{irt}, && (12) \\ &= b_{irt}p_{irt} + \sum_{l=0}^{\mathcal{L}-1} \alpha_l n_{\mathcal{G}_{irt}}^{-1} \sum_{j \in \mathcal{G}_{irt}} e_l(d_{ijrt}^C) p_{jrt} + u_{irt}^*, && (13) \end{aligned}$$

where d_{ijrt}^C contains the continuous distance measures, $\mathcal{G}_{irt}$ is the set of rival brands of brand i in region r at time t, $n_{\mathcal{G}_{irt}}$ is the number of such brands, the e_l's are the series expansion functionals and the α_l's the corresponding coefficients. u_{irt}^* includes both u_{irt} and the portion of the expansion which is not estimated. What is left is a model linear in coefficients with some endogenous regressors.

Pinkse, Slade and Brett (1998) have shown that both the coefficient estimators of the remaining regressors and the estimator of g have limiting normal distributions. The variance/covariance matrix is consistently estimable even though errors can be correlated across time and space. The procedure suggested by Pinkse, Slade and Brett (1998) is similar to the White (1980) or Newey–West (1987) covariance estimators.

Instead of only putting squared residuals on the diagonal of the variance matrix, as in White (1980), we also include cross products of residuals in some of the off–diagonal elements. The cross products correspond to the observations that we expect to have the greatest residual correlation. For consistency, the number of cross products thus included should increase with the sample size, albeit at a slower rate.

Since the expansion terms are interacted with rival prices, the number of endogenous regressors increases with the sample size. Additional instruments can be generated in the same way as if the model were fully parametric: expansion terms can be interacted with rival prices in the other region and/or with exogenous rival characteristics.

A.2 Some Identification Issues

The issue of identification is somewhat different from that in Pinkse, Slade and Brett (1998). First, the expansion is here in terms of variables that can also enter the X–part of the regression model. Second, we now have the potential for an infinite number of rivals (in the limit) at a finite distance from each brand. For example, alcohol contents are unlikely to fall outside of the range 2% to 6%, whereas geographic distance support was assumed to increase with the sample size in our earlier work.[56]

If the number of rival brands at a finite distance increases to a finite limit, then identification–related issues are addressed in our earlier paper. If the number of rival brands at a finite distance increases without bound with the sample size, then the influence of each individual brand is assumed to be asymptotically negligble. In essence, one is then estimating a conditional mean, where the conditioning variable is the brand's location in taste space, say its alcohol level and perhaps the product group to which it belongs.

Since alcohol can also enter as an X–regressor it is not immediately obvious that g is identified, even if alcohol only enters X linearly. However, provided that price distributions are different across regions and/or time periods and if g is the same across regions and time periods, then g can still be identified. For instance, a regression with dependent variable $q_{i2t} - q_{i1t}$ eliminates the alcohol–component of X as well as any time dummies, but not g. Combinations are also possible to simultaneously eliminate time and region fixed effects.

The above procedure is not necessary if discrete distance measures (such as product groupings) are used in g, but no corresponding product dummies are included in X, which is the case in the results that we present in section 7. In general, the procedure will not work well if price distributions and/or locations in taste space do not vary much across categories.

[56]Commonly used terminology is 'fill–in asymptotics' versus 'increasing domain asymptotics'.

B Calculation of Endogenous Common Boundaries

The procedure for determining endogenous common boundaries involves a grid search over possible values of the utility–loss parameters b_a, b_c. For each set of values (b_a, b_c) market areas are computed. The size of the market area (in $[0,1] \times [0,1]$) of each brand is then matched up to the corresponding fraction of the sales volume. The market areas corresponding to the value of (b_a, b_c) that minimizes an absolute loss function are then used to determine common boundary relationships.

Below we describe the procedure for finding market areas for specific (b_a, b_c). The procedure consists of three steps detailed in appendices B.1 through B.3. In the first step, described in appendix B.1, market areas are computed for each observation without regard for the fact that the entire market is contained in $[0,1] \times [0,1]$. In the second step (appendix B.2) market areas are 'cropped' to lie inside $[0,1] \times [0,1]$. In the third and final step, which is described in appendix B.3, the sizes of the market areas are computed.

B.1 Determining Market Areas

We first ignore the fact that taste space is $[0,1] \times [0,1]$ and determine market areas that possibly extend infinitely far. Each market area is a convex polygon (possibly extending to infinity) and contains the set of points at which the utility loss of brand i is less than that of all other brands.

We carry out the following procedure for each brand i.

1. Determine any brands $j \neq i$ with which i shares a boundary extending to infinity. Brands i and j share a common boundary if the set of points at which the utility loss of both brands is the same and is no greater than that of any other brand. The common boundary extends to infinity if the afore–mentioned utility loss can be made arbitrarily large. The number of brands $j \neq i$ with which brand i shares an infinite border is either zero or two.

2. If there are no brands $j \neq i$, for which i and j have common boundaries that extend to infinity, then find a 'corner point' of the market area of i. A corner point is a point at which the utility loss of distinct brands i, j, t is the same and is no greater than that of any other brand. If brand i has no corner points, the imputed size of its market area for the utility–loss parameters used is zero, and the procedure can go on to the next brand.

3. Now find the remaining corner points to complete the convex polygon. There is one other corner point involving brands i, j (and not involving t in case i and j do not share a boundary of infinite length). Find this corner point, which is the next corner of the polygon and involves brands i, j, s, $s \neq i, j, t$. The corner point after the (i, j, s) one involves brands i, s and a third brand, which needs to be determined. Repeat the procedure until the polygon is complete or until the other infinite boundary is reached.

B.2 Cropping

The cropping procedure is used to eliminate all parts of the uncropped market areas that extend outside $[0,1] \times [0,1]$. A full description of the cropping procedure would be too lengthy to include in this paper, but is available from the authors upon request. All brands whose market areas computed in section B.1 are completely outside the box are added to the list of brands with zero market area. Note that brands are not necessarily located inside their own market area.

B.3 Computing Market Area Sizes

We compute areas by noting that a convex polygon is made up of a number of triangles. The area of a triangle is easily computed. Assume that ν_1, ν_2, ν_3 are corner points of a triangle, then $\nu_4 = (1-\alpha)\nu_1 + \alpha\nu_2$, with $\alpha = (\nu_3 - \nu_1)^T(\nu_2 - \nu_1)/||\nu_2 - \nu_1||^2$, is the orthogonal projection of ν_3 onto the line segment connecting ν_1 and ν_2. Then the area of the triangle is $||\nu_1 - \nu_2||\ ||\nu_3 - \nu_4||/2$. We have carved the polygon into triangles as follows. Pick a corner point ν_1^* and move along the polygon labeling the remaining corner points in order $\nu_2^*, \ldots, \nu_{n_\nu}^*$ with n_ν the number of corner points of the polygon. The triangles are those with corner points $\nu_1^*, \nu_2^*, \nu_3^*$, $\nu_1^*, \nu_3^*, \nu_4^*$, $\nu_1^*, \nu_4^*, \nu_5^*$, etcetera.

Table 1:
Selected International Comparisons

1A: Consumption per Head and Imports[a)]

	Country	1975	1985	1995
Consumption/Head (Liters)	UK US Canada France Germany	118.5 81.8 87.0 41.3 147.8	109.2 89.7 82.2 40.1 145.4	100.9 83.5 66.5 39.1 137.7
Imports (%)	UK US Canada France Germany	4.4 1.1 0.6 8.6 0.8	6.0 4.3 4.4 11.1 1.2	8.8 6.0 3.3 15.4 2.3

1B: Draft Sales and Average Strength[a)]

	Country	1991	1996
Draft Sales (%)	UK US Canada France Germany	71 11 10 25 23	66 10 12 23 20
Average Strength (%)	UK US Canada France Germany	4.0 4.5 5.0 4.6 5.0	4.1 4.6 5.0 5.0 5.0

1C: Three-Firm Concentration Ratios in 1985[b)]

UK	US	Canada	France	West Germany (CR_5)
47	74	96	81	28

a) Source: The Brewers and Licensed Retailers Association (BLRA)
b) Source: The Monopolies and Mergers Commission (MMC)

Table 2:

Selected UK Beer Statistics[a)]

Year	1970	1980	1990	1997
% Lager	7	31	51	59
Real Ale/Total Ale %	NA	43	56	60
% On Premise Sales	90	88	80	72
# of Brewering Companies	96	81	65	61

Table 3:

National Market Shares of National Brewers
All Brands, Draft and Packaged[b)]

<table>
<tr><th>Brewer</th><th>1985
Market Share</th><th>1991
Market Share</th><th>1996
Market Share</th></tr>
<tr><td>Allied Lyons</td><td>13</td><td>12</td><td rowspan="2">14</td></tr>
<tr><td>Carlsberg</td><td>NA</td><td>4</td></tr>
<tr><td>Bass</td><td>22</td><td>22</td><td>23</td></tr>
<tr><td>Courage</td><td>9</td><td rowspan="2">19</td><td rowspan="3">28</td></tr>
<tr><td>Grand Metropolitan</td><td>11</td></tr>
<tr><td>Scottish & Newcastle</td><td>10</td><td>11</td></tr>
<tr><td>Whitbread</td><td>11</td><td>12</td><td>13</td></tr>
<tr><td>Total</td><td>77</td><td>78</td><td>78</td></tr>
</table>

a) Source: The Brewers and Licensed Retailers Association (BLRA)
b) Source: The Monopolies and Mergers Commission (MMC)

Table 4:

Summary Statistics by Product Type[a)]
London and Anglia Draft Beer
Brands in Sample

4A: Three Major Groups

Variable	Units	Lager	Stout	Ale
Average Price	Pence per pint	175.3	184.0	154.6
Total Volume	100 barrels	8732	1494	4451
Average Volume	100 barrels	47.5	67.9	18.7
Market Share	%	59	10	31
Average Coverage	%	10.1	31.3	6.3
Alcohol Content	%	4.3	4.1	3.9
Number of Brands		25	4	34

4B: Ales

Variable	Units	Cask Conditioned ('Real')	Keg
Average Price	Pence per pint	158.3	148.2
Total Volume	100 barrels	3092	1359
Average Volume	100 barrels	20.3	15.8
Market Share	%	21.5	9.5
Average Coverage	%	7.0	5.2
Alcohol Content	%	4.1	3.7
Number of Brands		21	13

[a)] Averages taken over brands, regions, and time periods

Table 5: Summary Statistics by Establishment Type and Region
Draft Beer
Brands in Sample

5A: London

Establishment Type	Average Price	Average Volume	Average Coverage
Multiples	174.5	42.7	11.3
Independents	160.9	58.0	7.2

5B: Anglia

Establishment Type	Average Price	Average Volume	Average Coverage
Multiples	168.5	10.4	10.5
Independents	155.6	20.4	7.7

Table 6: IV Demand Equations

6A: Equations with a Single Distance Measure

Intercept (a_i)						*Own-Price* (b_{ii})				*Rival-price* (b_{ij})		
CONS	LCOV	ALC	PUBM	PER1	REG1	PRICE	PRCOVR	PRPREM	PRNCBX	VAR.	COEF.	t STAT
-	+	+	-	+	+	-	+	-	-			
**	**	†	**		**	†	**	*	†	None		
*	**	†	**	*	†		**	†	*	RPSHARE	21.3	2.1
**	**	†	*		**	**	**		†	RPPROD	0.82	2.6
	**	†	**		**		**	*	†	RPBREW	-0.40	-1.1
**	**		**		**	†	**		†	RPALC	0.16	0.7
			**		**					RPCOV	-1.38	-1.7
**	**		**		**		**	*	†	RPCBN	0.04	0.7
**	**	*	**		**	*	**	*	†	RPCBX	-0.08	-1.7
**	**		**		**		**	*	†	RPNNN	0.06	1.2
**	**	†	**		**	†	**	*	†	RPNNX	0.008	0.2
Semiparametric Estimates with RPPROD[a)]												
**	**		*		**		**		*	3 expansion terms		
**	**		†		**		**		**	5 expansion terms		

** denotes Significance at 1 %
* denotes significance at 5 %
† denotes significance at 10 %
[a)] Standard errors corrected for heteroskedasticity and spatial correlation of unknown form

6B: IV Equation With Multiple Distance Measures[a)]

RPPROD	RPBREW	RPALC	RPCBN	RPNNN
0.82 (2.5)	-0.19 (-0.5)	0.16 (1.2)	0.02 (0.3)	0.05 (0.9)

a) Asymptotic t statistics in parentheses

6C: IV Equation Used in Evaluation of Games[a) b)]

Intercept (a_i)						*Own-Price* (b_{ii})				*Rival-price* (b_{ij})	
CONS	LCOV	ALC	PUBM	PER1	REGL	PRICE	PRCOVR	PRPREM	PRNCBX	RPPROD	RPALC
-159.1 (-4.0)	60.3 (11.7)	8.80 (0.7)	-11.0 (-1.9)	3.81 (0.8)	31.5 (6.4)	-1.13 (-2.9)	0.17 (7.8)	-0.03 (-0.1)	-0.12 (-2.7)	0.71 (2.6)	0.22 (1.1)

a) Asymptotic t statistics in parentheses

b) Standard errors corrected for heteroskedasticity and spatial correlation of an unknown form

Table 7:

Own and Cross-Price Elasticities for Selected Brands[a)]

London

Brand *Alcohol Content* *Product Type* *# Neighbors*	***Tennants Pilsner*** *3.2%* *Reg. Lager* *12*	***Lowenbrau*** *5.0%* *Prem. Lager* *8*	***Stella Artois*** *5.2%* *Prem. Lager* *8*	***Courage Best*** *4.0%* *Real Ale* *15*	***Greene King IPA*** *3.6%* *Real Ale* *9*	***Toby Bitter*** *3.3%* *Keg Ale* *12*	***Websters Yorks Bitter*** *3.5%* *Keg Ale* *8*	***Guiness*** *4.1%* *Stout* *2*
Tennents Pilsner	-4.80	0.095	0.090	0.006	0.007	0.011	0.009	0.006
Lowenbrau	0.034	-2.49	0.042	0.002	0.001	0.001	0.001	0.002
Stella Artois	0.045	0.059	-3.10	0.003	0.002	0.002	0.002	0.003
Courage Best	0.002	0.002	0.002	-2.79	0.031	0.002	0.003	0.005
Greene King IPA	0.032	0.019	0.020	0.426	-12.64	0.031	0.045	0.041
Toby Bitter	0.015	0.004	0.005	0.007	0.009	-4.87	0.229	0.008
Websters Bitter	0.004	0.002	0.002	0.003	0.004	0.078	-2.20	0.004
Guiness	0.001	0.001	0.001	0.002	0.001	0.001	0.001	-0.93

a) Evaluated at observed prices and quantities

Table 8:

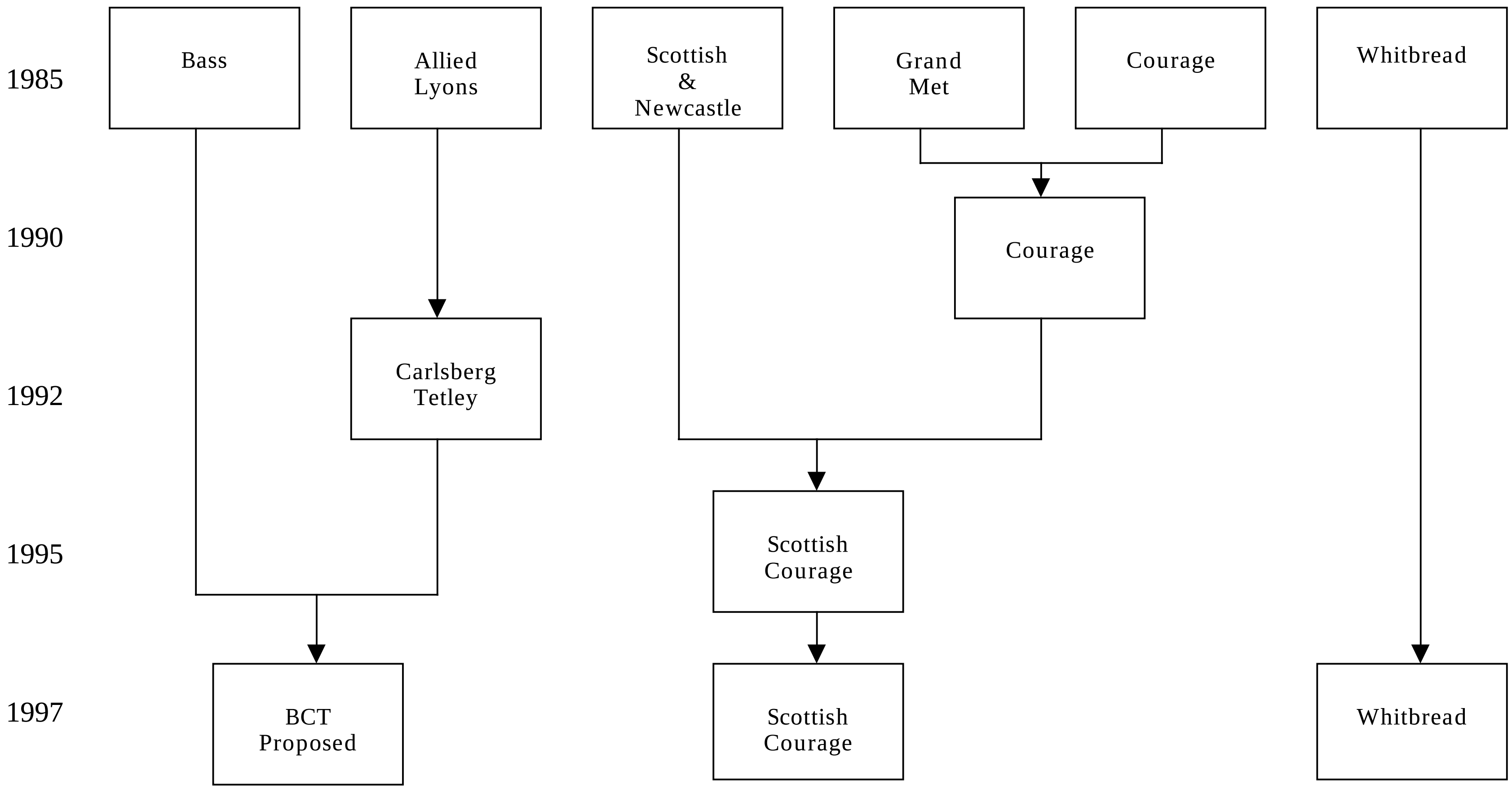
Nash-Equilibrium Prices

London

	Actual	*Status Quo*	*Before*	% Δ	*After*	% Δ
Mean	167.8	168.4	167.4	-0.6	173.5	+3.0
Standard Deviation	20.2	29.5	22.1		30.2	

Figure 1:

Developments in the UK Brewing Industry



Source: MMC

Figure 2: Endogenous Market Areas for London

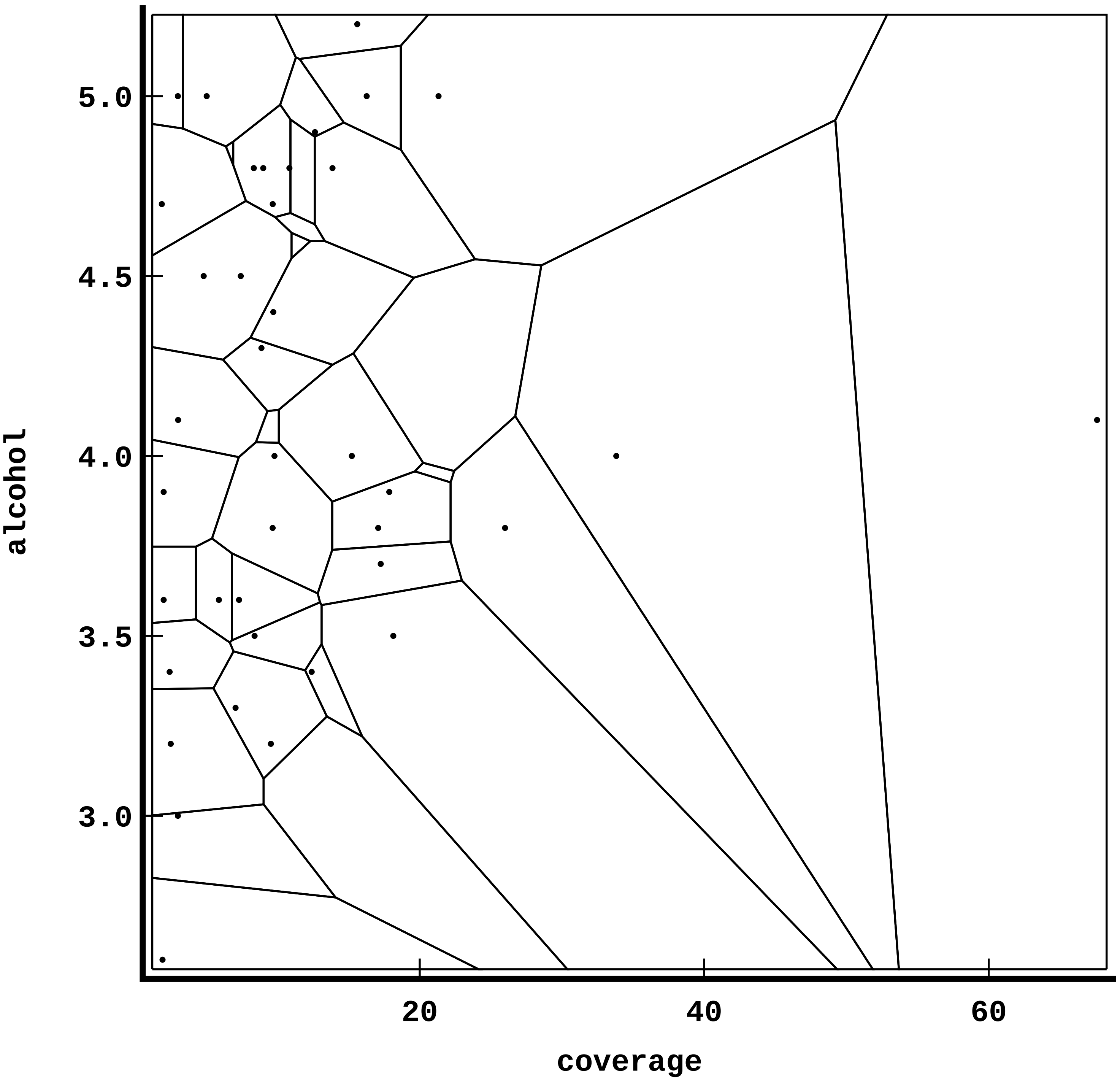


Figure 3A: g, Same Product Type rivals (3 expansion terms)

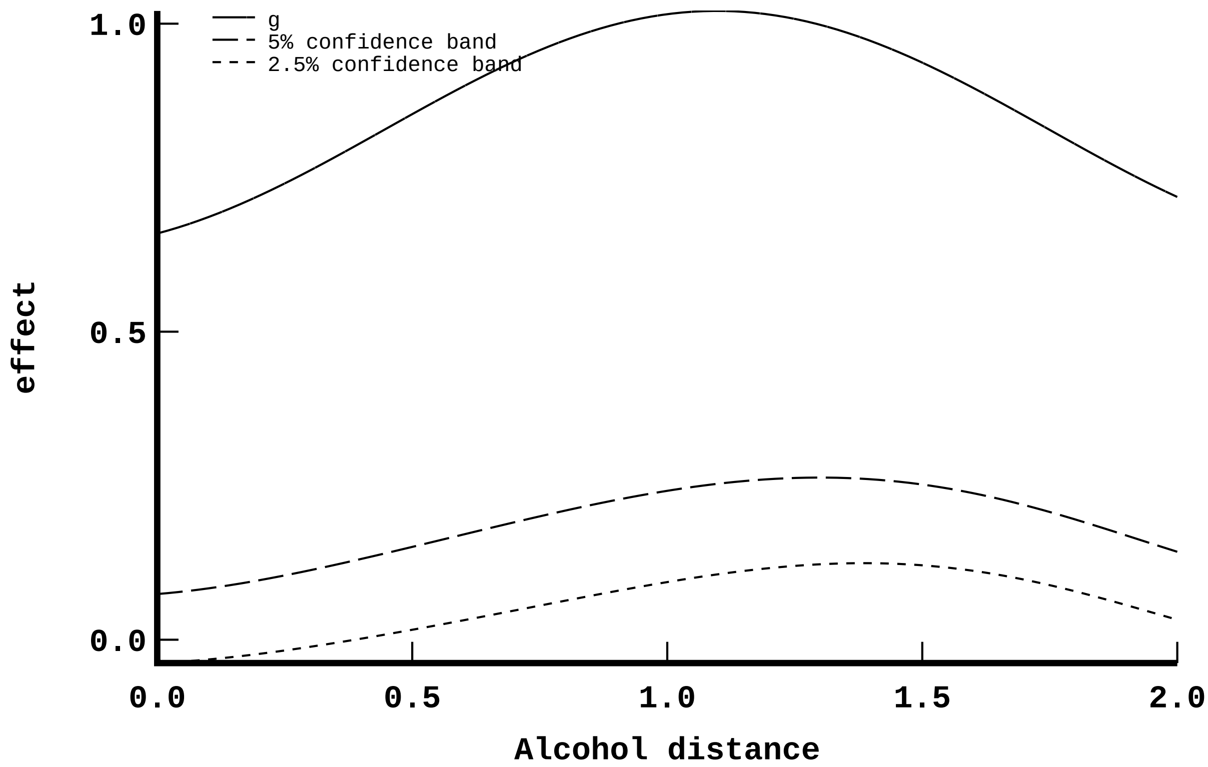


Figure 3B: g, Same Product Type rivals (5 expansion terms)

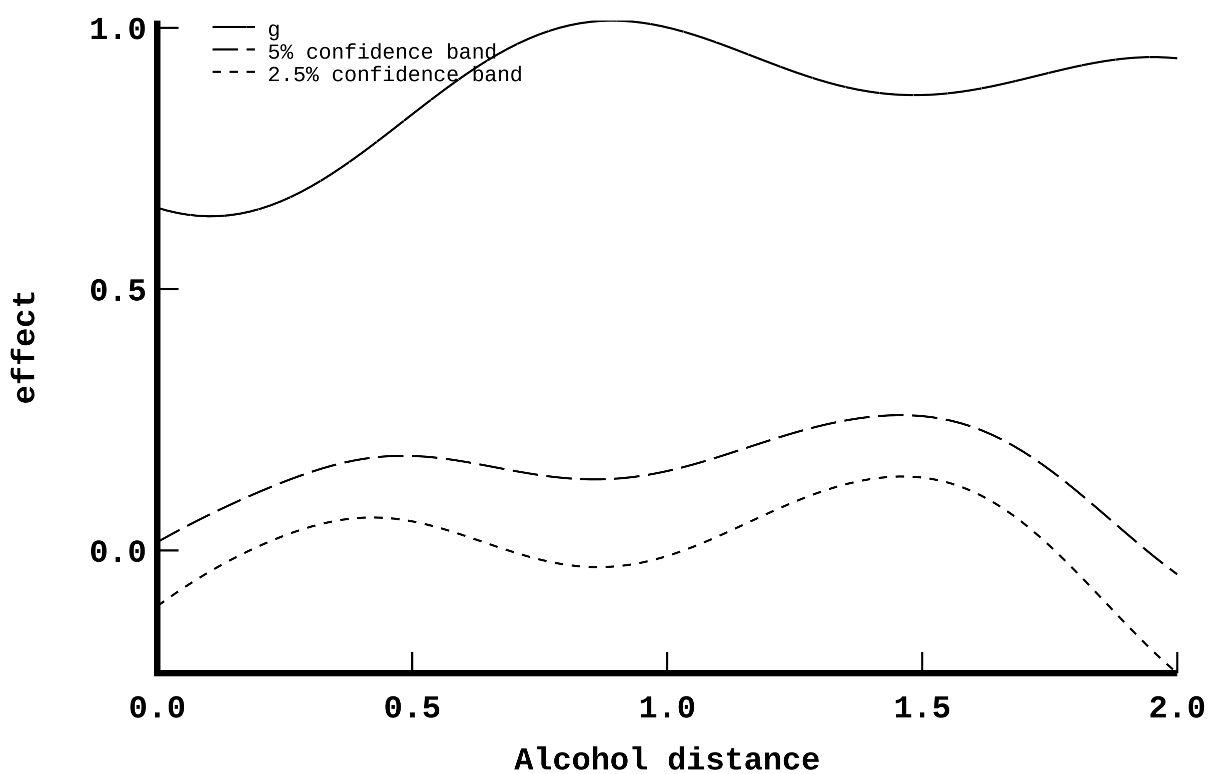


Figure 4: Histogram of Market-Conduct Parameters, London