Competition in a spatially-differentiated product market with negotiated prices*

Walter Beckert* Howard Smith† Yuya Takahashi‡

August 2021

Abstract

In many competitive markets the buyer makes a choice between differentiated products and pays a negotiated price. We develop for estimation a discrete-choice model of differentiated product demand, where prices are the outcome of negotiations. The model is consistent with non-cooperative models of bargaining with multiple potential sellers. We show that when the buyer's utility has GEV disturbances the model has a tractable likelihood function for use with transaction-level data giving the selected product and its price for each transaction. We estimate the model using data from the UK brick industry and use it to measure market power and analyze mergers. We measure the contribution of spatial differentiation and ownership concentration to the distribution of market power across individual transactions. In counterfactuals we find that, relative to uniform-pricing, individually-negotiated pricing leads to reductions in mean markups and merger effects, although markups and merger effects increase in a minority of transactions.

Keywords: individualized pricing, bargaining, price discrimination, spatial differentiation, merger analysis, construction supplies

*We thank participants of several conferences and seminars for comments. We are grateful to Pat Bajari, Ken Binmore, Allan Collard-Wexler, Vince Crawford, Isis Durremeyer, Matt Grennan, Gautam Gowrisankaran, Joe Harrington, Tom Holmes, Jean-Francois Houde, John Kennan, Robin Lee, Nate Miller, Eugenio Miravete, Nicola Pavanini, Markus Reisinger, Holger Sieg, Bernardo da Silveira, Andrew Sweeting, Mariano Tappata, Greg Taylor, Bob Town, Ali Yurukoglu, and construction industry experts, for discussion. *Birkbeck College, University of London and Institute for Fiscal Studies †Department of Economics, Oxford University, CEPR and Institute for Fiscal Studies. ‡University of Washington-Seattle. We are grateful to Segye Shin for research assistance, and for financial assistance to the John Fell Fund at Oxford University and ESRC grant number ES/M007421/1.

1 Introduction

In many competitive markets the buyer makes a choice between differentiated products and negotiates an individualized price. This is common in decentralized markets for intermediate goods where buyers and sellers are few. In 2010 the US Merger Guidelines were revised to include a section on markets with this feature.[1]

The theoretical literature suggests that individually-negotiated pricing can make a major impact (relative to uniform pricing) on market power in oligopoly markets.[2] The impact depends, among other things, on product differentiation and the bargaining power of sellers—e.g. in the duopoly case where sellers can make take-it-or-leave-it (TIOLI) offers to individual buyers, and differentiation is specified as Hotelling, individualization causes markups to fall for all buyers, and mean markups to fall by 50% (see Thisse and Vives (1988)). If product differentiation is specified differently, markups may rise for some buyers (see Stole (2007)). Individualized pricing can also change (relative to uniform pricing) the effect of mergers on markups (see Cooper et al. (2005)).

A distinctive feature of competition with individualized pricing is the prominent role in markup determination played by the first-best and runner-up goods, ranked in terms of the surplus from trade. This feature is found in non-cooperative models both where sellers set TIOLI prices (see Thisse and Vives (1988)), and where buyers have bargaining power (see Binmore (1985), Bolton and Whinston (1993) and Manea (2018)), and contrasts with uniform-price competition, where markups depend on market-level elasticities and ownership portfolios (see Nevo (2001)). With multi-product firms, the relevant definition of the runner-up good is the highest-surplus good that is not co-owned with the first-best good, so that an increase in multi-product ownership by means of a merger can add to market power if the runner-up good is a more distant substitute as a consequence. The importance of the runner-up good is recognized in antitrust practice—e.g. the 2010 US Merger Guidelines suggest that, with individualized pricing, anti-competitive effects are likely to arise for a buyer if merging parties jointly occupy that buyer's (pre-merger) first-best and runner-up status.

[1] Section 6.2 on "Bargaining and Auctions" notes that "in many industries, especially those involving intermediate goods and services, buyers and sellers negotiate to determine prices" and "buyers commonly negotiate with more than one seller, and may play sellers off against one another." US merger cases where this was relevant include sellers of consumer-generated ratings platforms, whose clients include online retailers (*Power Reviews/Bazaarvoice*, 2014), marine water treatment products, whose clients run fleets of ships (*Wilhelmsen/Drew Marine*, 2018), and private label breakfast cereals, procured by retailers (*Post Holdings/TreeHouse Foods Inc*, 2020); in the EU individually-negotiated pricing was relevant in the *GE/Honeywell* avionics merger case in 2001. See Sweeting et al. (2020) for a discussion of *Post Holdings/TreeHouse Foods Inc* and Nalebuff (2009) for a discussion of *GE/Honeywell*.

[2] We use *individualized* and *negotiated* (interchangeably) to describe pricing either where sellers make take-it-or-leave-it offers or where buyers and sellers both have bargaining power.

An important group of markets in which individualized pricing is found is construction materials—e.g. cement, steel, bricks, etc.[3] Markets for these materials have seen public policy discussion in at least two areas. The first area is the merits of price discrimination; a well-known debate, for delivered products, which dates back at least to *FTC vs. Cement Institute* 1948, compares uniform pricing, where the price before transport cost is the same for all buyers, with discriminatory pricing, where prices depend on buyer location (see Thisse and Vives (1988)). The second area is mergers and market concentration; there have been many recent merger and market inquiries.[4] In this paper we consider the brick manufacturing industry in Great Britain. In CC (2007) the Competition Commission (CC) investigated a merger between two of the four manufacturers in this industry. They judged the market to be highly concentrated—with a two-firm concentration ratio of 0.60, and a Herfindahl-Hirschman Index (HHI) of 2113—but, despite this, assessed its profitability as at or below average, for industries with comparable risk, and approved the merger, even though the implied HHI increase exceeded the normally-acceptable threshold in its merger guidelines (implicitly based on uniform pricing). In effect the CC took the view—in line with some of the theoretical literature noted above—that competition in this market is more intense, and the merger less of a concern, than usual for a market at its concentration level.[5]

This paper makes two main contributions. First, we develop for empirical analysis a model of demand for differentiated products in which the buyer negotiates prices with multiple sellers and sources from one of them. The model is micro-founded in the existing theoretical literature on non-cooperative bargaining with single-sourcing but has not previously been estimated empirically in the discrete-choice literature. We derive a tractable likelihood expression which can be used with micro data giving the observed choice and price in each transaction. Second, we estimate the model using data from the UK brick industry, and use it to measure market power and analyze counterfactual changes to pricing policy and market concentration.

In the model, the buyers are house-building firms, with multiple projects in separate locations, and the suppliers are manufacturers of multiple differentiated products. Each

[3]See CMA (2016) paragraph 6.26 for a description that applies to aggregates, cement, and concrete and paragraph 7.170 which states "cement prices are negotiated with customers, and can depend on [...] delivery distance, type of cement, size of order and the customer's bargaining power."

[4]Examples include the US cement merger case *Holcim Ltd. and Lafarge S.A.* in 2017 and the UK construction supplies inquiry (CMA (2016)).

[5]CC (2007) reports (paragraph 5.47) that the current HHI was 2,113 and the HHI change implied by the merger was 390; the CC merger guidelines regard a market with an HHI above 1,800 as highly concentrated, and (in such a market) identifies an increase in HHI of more than 50 as giving potential competition concerns; summing up they say that "the market is thus already highly concentrated and would become more so if the merger were to proceed." The assessment that profits are at or below normal levels is in Appendix B of CC (2007).

project requires cladding, using a brick product or the outside good. Products are valued differently across projects. For each project, a price is negotiated for the first-best and runner-up products. In our solution concept the buyer negotiates bilaterally with each of the two sellers. In each bilateral negotiation the agents agree a price implied by bilateral Nash bargaining, in which the disagreement point is the alternative of not buying any brick product, and the buyer has an outside option (see Binmore et al. (1989)) of buying the other product at its anticipated price. Equilibrium is achieved when the two bilateral negotiations are mutually consistent. In equilibrium the buyer buys the first-best product at a negotiated price which is the lower of (i) the price implied by standard bilateral Nash bargaining with the first-best product's seller and (ii) the Bertrand-Nash TIOLI price.[6] This choice and price outcome is micro-founded in the non-cooperative multi-seller bargaining models in Binmore (1985), Bolton and Whinston (1993), and Manea (2018).

To estimate the model, we use a dataset of 13,788 transactions between manufacturers and house-building firms, giving the chosen product, price, production and delivery locations, volume, transport costs, and brick characteristics. We also have plant-month production cost data, which we use in model validation. The patterns in the data indicate that prices vary across transactions, controlling for brick product, house builder and year, and that spatial differentiation is important.

There are two main econometric challenges. First, we observe neither the runner-up product nor (unlike standard discrete choice settings) the prices the buyer would have paid for products that are not chosen. Second, since the price of the chosen product is individualized, it is correlated with individual-specific tastes which are unobserved to the econometrician and affect the choice of product, so that, conditional on choice of product, the regressors in the pricing equation (such as product characteristics) are endogenous. To overcome these challenges, we estimate the choice and pricing parts of the model jointly, and integrate out unobserved tastes along with their implications for the runner-up product and first-best price. Since our application has many products, this is a high-dimension problem. We show that when idiosyncratic tastes are characterized by a Generalized Extreme Value (GEV) distribution there is a tractable likelihood expression for the joint probability of the observed choice and individualized price.[7]

The estimated model implies that the case of TIOLI prices, nested in the bargaining model, is rejected in a likelihood ratio test. As an external validity check on the estimated model, we find a good match between the costs implied by our estimates

[6] The model accommodates alternative assumptions for the disagreement point. In the empirical analysis we perform a robustness analysis where the disagreement point is the runner-up good.

[7] A separate challenge is that transactions data do not include information on demand for the outside good. To overcome this we calculate market shares for the outside good using data from another source.

and external plant-month level cost data supplied by the manufacturers. The estimated model also fits the data well in terms of the distribution (across transactions) of prices and transportation distances. We find that markups are low on average but vary quite widely across transactions; price-cost margins (PCM), in Lerner index form, have a mean of 0.08 and a coefficient of variation of 0.74. We find that location plays a role in markup variation: sellers tend to set higher margins to buyers that are relatively close, extracting some of their location advantage. Product ownership also plays a role: monopoly power from multi-product ownership, sometimes referred to as the portfolio effect, is much more relevant for some buyers than others.

We consider counterfactual questions in the two policy areas we noted above. The first is the effect of pricing policy. We find that average markups increase if there is a policy switch to uniform pricing. This holds for a wide range of potential market structures as well as the observed market structure, and is in line with the view that uniform pricing adds to market power. The changes in markups in individual transactions, however, vary widely, and in a minority of transactions markups fall. This contrasts with the all-markups-rise result in the Hotelling specification of Thisse and Vives (1988). At the observed market structure, for example, a switch to uniform pricing increases mean markups by 34%, and, in the distribution of percentage price changes, the bottom and top deciles are -6.57% and 14.32% respectively.

The second question is the effect on market power of market concentration. With individualized pricing, other things equal, a change in product ownership does not influence a transaction's markup unless it changes the runner-up good for the transaction—e.g. by in a merger reassigning ownership of the (pre-merger) runner-up good to the first-best product's seller. To evaluate the importance of market power from product ownership, at the observed market structure, we demerge to the case of single-product manufacturers. Total manufacturer surplus falls substantially (by 24%) but the impacts are unequal across transactions: in the distribution of markup reductions, the top decile is 30 times greater than the bottom decile. This shows that the relevance of the first-best seller's product portfolio varies greatly across individual transactions. The remaining counterfactuals are pairwise mergers of the manufacturers. The merger of the two largest firms in terms of market share generates an increase in total manufacturer surplus in the industry of 20%. However, markup increases are very unequal across transactions. Finally, we find that a change to pricing policy has a major impact on the effects of mergers: comparing the same mergers under the two pricing policies, we find that individualized pricing abates markup-increasing effects of mergers on average but makes them worse in some transactions.

Related literature The theoretical literature on the impacts on market power of oligopoly price discrimination with differentiated products dates at least from Thisse and Vives (1988), Holmes (1989) and Corts (1998). Our paper builds on the empirical contributions in Miller and Osborne (2014) and D'Haultfoeuille et al. (2017)—which combine the differentiated products demand specification in Berry et al. (1995) with oligopoly price discrimination—by extending the analysis to individualized (rather than third-degree) discrimination, by allowing buyers to have bargaining power (as opposed being price-takers), and in the use of transaction-level (rather than market-level) data.

Our paper relates to the empirical bargaining literature based on the Nash-in-Nash (NiN) solution in Horn and Wolinsky (1988). The papers in this literature, which are often applied to media and healthcare industries, include Chipty and Snyder (1999), Draganska et al. (2010), Crawford and Yurukoglu (2012), Grennan (2013), Gowrisankaran et al. (2015), Ho and Lee (2017), Crawford et al. (2018), and Dubois et al. (2019). The NiN solution concept has been given non-cooperative micro-foundations in Collard-Wexler et al. (2019). There are two main differences between our paper and this literature. First, the buyers in our model single-source (as in standard discrete-choice settings), so some sellers are rejected by the buyer, whereas in the the NiN framework the buyers trade with all the sellers. The bargaining solution in our model thus accounts for the impacts of sellers with whom the buyer negotiates but whose price the buyer rejects. The bargaining solution we propose is micro-founded in the non-cooperative multi-seller single-sourcing bargaining models of Binmore (1985), Bolton and Whinston (1993) and the simple (i.e. no intermediary) version of the model in Manea (2018). Second, the data that the econometrician can observe are different in our setting. In the NiN framework, since each buyer trades at each negotiated price, a price and a quantity is in principle observed for all products that are in negotiations. Together with the passive beliefs assumption—i.e. that a disagreement with one seller leaves unchanged the prices negotiated with other sellers—the researcher may use this information to estimate the buyer's gains from trade in each bilateral negotiation. In our model by contrast only one of the choice alternatives is selected for trade and hence we must account for the inherent unobservability of the runner-up product and its negotiated price.

Ho and Lee (2019) develop a bargaining solution, Nash-in-Nash with Threat of Replacement (NNTR), which extends the NiN framework to give multi-sourcing buyers an incentive to exclude firms from their networks. The runner-up seller in our model and the excluded firms in the NNTR solution play the role of an outside option. Our framework is not intended for use with multi-sourcing firms, and has a different estimation approach, which extends the random utility discrete choice framework in Berry et al. (1995) to allow for negotiated prices, deriving a convenient form for the joint probability of a discrete choice and negotiated price.

The paper builds upon the empirical literature on individualized pricing with single-sourcing buyers, including Allen et al. (2019), Marshall (2020), and Salz (2020). Our model differs in three main respects. First, we have differentiated products and multi-product firms. Second, in our model the agents do not search, which suits applications with few buyers and sellers and minimal product or process innovation. Third, the buyers in our model are not price-takers, allowing them to appropriate a greater level of surplus from the seller than otherwise.

More generally the paper is related to the literature on auctions in the presence of transportation costs, e.g. Porter and Zona (1999), and those with GEV taste shocks, e.g. Brannman and Froeb (2000). Miller (2014) develops a theoretical model of scoring auctions with Type-1 EV consumers, which is nested in our model, and includes an extension which is equivalent to an alternative bargaining specification which we use as a robustness check.[8] Finally, the paper is related to the empirical literature on mergers when prices are not uniform across buyers: Gowrisankaran et al. (2015) consider mergers in a structural Nash-in-Nash bargaining model (with multi-sourcing buyers) and Allen et al. (2014) use reduced form methods in a market with consumer search.

2 The market and data

Institutional details Bricks have been used in construction for millennia. The largest buyers of bricks in Great Britain are national house-building firms, which buy bricks directly from manufacturers for cladding purposes. We study transactions of domestically-produced bricks bought by these firms, hereafter *buyers*. In any year each buyer develops multiple housing projects of different sizes in different locations. The buyers are responsible for all the key aspects of their projects including choice of cladding. The buyers source from different manufacturers for different projects. The market is concentrated: there are four main manufacturers with an 85% share of brick sales (CC (2007), paragraph 5.46). Buyers negotiate prices that hold good for a given year; for any buyer the negotiated prices vary with the brick variety, quantity and project location. Third-party hauliers, arranged by the manufacturer, deliver the bricks to the project location and are paid separately.[9]

[8] We show that the likelihood function derived in our paper for the (baseline) bargaining model includes the case of the auction specification (which we refer to as the TIOLI model and is nested in the model) and can be adapted for the alternative bargaining specification.

[9] Hereafter *bricks* refers to bricks used for cladding. Cladding is 80-90% of brick production (CC (2007), paragraph 4.2). Alternative cladding materials include timber, stone, and plaster. Direct-supply bricks are about 20% of brick production; the rest is sold through intermediaries whose final

	Mean	SD
A: Price, quantity, distance, transport costs		
Price (£/1000 bricks)	182.256	24.843
Quantity (1000s)	84.072	83.950
Delivery distance (100km)	0.109	0.075
Transport cost (£/1000 bricks)†	23.850	10.530
B: Agent size (#transactions per year)		
Manufacturer	861.750	755.180
Buyer	231.864	221.038
C: Variety characteristics of chosen product: aesthetic and technical		
Color: red (indicator variable)	0.718	0.450
Shaping method: wire (indicator variable)	0.720	0.449
Strength, Newton/square meter (100s)	0.398	0.182
Water absorption, percentage units (100s)	0.143	0.043
D: Weather and input prices of project's region-year		
Frost: Average monthly (#days with frost, by region)	4.669	0.619
Rainfall: Average daily rainfall (mm/sq meter, by region)	2.396	0.742
Wage: Gross household income/head (£1000s, by region-year)	13.786	1.352
Fuel: annual natural gas index (1990=100, by year)‡	0.991	0.198
Fuel: annual haulage price (£/L, by year)‡	0.861	0.069
E: Competition [notation in italics used in Table 2]		
#Manufacturers within 50 km: *N(50)*	1.555	1.182
#Manufacturers within 100 km: *N(100)*	2.680	1.044
Distance advantage of nearest manufacturer w.r.t. next-nearest: *DA* (km)	33.986	42.381

Notes: 13,788 observations. †11,855 observations. ‡*BEER Quarterly Energy Prices Report* (2008): Gas price index Table 3.3.1 (three-year moving average); Haulage fuel price, Table 4.1.2. Appendix C.3 discusses product characteristics and weather data. Regions are the NUTS1 definition.

Table 1: Transactions data: summary statistics

Description of the data We use a data set which records all deliveries of bricks from the four main manufacturers in Great Britain in the period 2003-2006. For each delivery we observe the date, variety (with unique production location), destination location, buyer, quantity, and payment. We treat a unique buyer-variety-destination-year as defining a project. We obtain the four main characteristics of each variety from the manufacturers' catalogs—color, shaping method, strength, and water absorption; the first two are aesthetic and the other two are technical. Transport costs to the buyer for each delivery are also recorded (for three of the manufacturers). We consider the largest 16 buyers, which account for 94.1% of direct-delivery volume in the data. We aggregate the data over deliveries within each year to buyer-variety-destination-year

customers are households or small builders, often for repair, maintenance and improvement of existing dwellings (CC (2007), paragraphs 4.42 and 4.47). Imported bricks are about 8% of volume (CC (2007), paragraph 4.21). For further discussion of institutional details see Appendix C.5.

level, which corresponds to a negotiated transaction, giving 13,788 transactions over four years sold from 36 plants; hereafter we refer to this as the transactions dataset.[10]

Since there are hundreds of varieties, and many are very similar, we define for choice modeling the less granular concept *product*, using unique combinations of the four brick characteristics above and the plant's location. This results in 75 products.[11]

Table 1 reports summary statistics from the transactions data. Panel A describes prices, quantities, distances, and transport costs. Panel B describes agent (manufacturers and buyers) size, measured by annual number of transactions. Panel C reports statistics for the main brick characteristics other than location. Panel D summarizes weather data in the region of the delivery location, which can affect the buyer's valuation of the technical characteristics, along with key input price data. Panel E reports two measures of competition: the number of manufacturers within a given radius of a project, and the distance between a project's nearest and second-nearest manufacturer.

Finally, we calculate the market share of the outside good: non-brick cladding, bricks from minor manufacturers, and imports. For each region-year market m this is given by $s_{m0} = (H_m - B_m)/H_m$ where H_m is the number of new houses and B_m is the number of new houses that use bricks from the top four manufacturers. We calculate H_m from official house-building data and obtain B_m using information on brick deliveries and an estimate of the number of bricks per house. See Appendix C.7 for details. The market share of the outside good has a mean of 0.272 and a standard deviation 0.141 across region-year markets. The number of buyers of the outside good is given by $N_{0m} = N_{Jm}s_{0m}/(1 - s_{0m})$ where N_{Jm} is the number of buyers of inside goods in region-year m in the transactions data.

Data patterns I: prices To characterize price variation, Panel A of Table 2 reports the R^2 and root mean square error (RMSE) for price regressions with dummies at alternative levels: none, year, variety-year, and buyer-variety-year. Column (i) uses the full set of brick transactions and—to help characterize intra-buyer price dispersion—column (ii) only includes observations with more than five transactions for each buyer-variety-year. Year effects explain only a small amount of price variation. Adding

[10] To prepare the transactions dataset we drop a shaping type (pressed, 1.2% of volume) and colors other than red and yellow (0.04% of volume) which are rarely used in new housing projects, products with a mean of less than 7.5 annual transactions (which removes a tail of low market share products which together are 4.2% of volume), low-quantity (<5000 bricks) deliveries (3.1% of volume), and, to avoid outliers, transactions with unit prices in the top and bottom percentiles. See Appendix C.4 for further details. See Beckert (2018) for a discussion of the data.

[11] To do this we discretize strength and water absorption—measured in N/m^2 and percent units respectively—using intervals of 5, resulting in 5 absorption and 13 strength levels, and use the mid-point of the interval as the product's characteristic. See Appendix C.3. See also footnote 13.

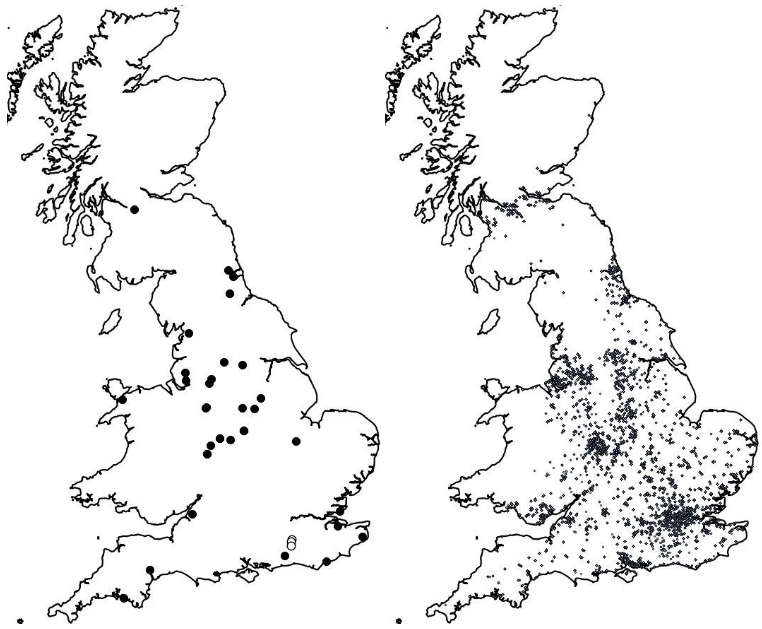
A: Price regressions with alternative controls					(i)		(ii)	
					R^2	RMSE	R^2	RMSE
Dummy variables included:	none				0.000	24.843	0.000	21.195
	year				0.118	23.340	0.130	19.771
	variety-year				0.775	11.780	0.816	9.098
	buyer-variety-year				0.918	7.114	0.867	7.740
Observations included					all observations		buyer-variety-year with > 5 locations	
#Observations					13,788		6,587	
Mean price (£/1000)					182.256		176.141	
B: Price regressions	(i)		(ii)		(iii)		(iv)	
Constant	59.371	(10.042)	59.492	(10.020)	63.673	(9.964)	63.856	(9.997)
Quantity (units 100,000)	-0.383	(0.133)	-0.421	(0.133)	-0.446	(0.132)	-0.454	(0.133)
Wage (units £1000)	8.281	(0.847)	8.270	(0.846)	8.107	(0.840)	8.299	(0.843)
Gas price (index)	27.200	(1.824)	27.239	(1.821)	27.499	(1.809)	27.084	(1.815)
ln(buyer size/seller size)	-2.510	(0.147)	-2.558	(0.147)	-2.446	(0.146)	-2.558	(0.146)
1[DA>DST], indicator	0.482	(0.237)	2.204	(0.293)				
N(DST), count					-1.531	(0.101)	-1.487	(0.124)
R^2	0.754		0.755		0.758		0.756	
DST:	20km		40km		50km		100km	

Notes. Dependent variable: price in £/1000 bricks. Panel A reports measures of fit (not adjusted for d.f.) for alternative specifications. Panel B: Observations: 13,788. Variety dummies in all regressions. Seller refers to manufacturer. Seller and buyer size, seller's distance advantage (DA), local seller count N(DST), and other variables, are as defined Table 1. Standard errors in parentheses.

Table 2: Results from unit price regressions

variety-year and buyer-variety-year effects absorbs more variation, but still leaves much unexplained—i.e. there is intra-buyer (cross-project) variation conditional on variety-year. Panel B explores the relationship between prices and variables that vary across projects. All specifications include variety dummies. The four specifications use two alternative measures of local competition: the distance-advantage DA of the nearest manufacturer, and counts $N(DST)$ of local manufacturers as defined in Table 1. The estimates indicate that prices are decreasing in quantity, increasing in input prices, decreasing with the buyer-seller size ratio, and that competition variables have the expected signs. While these estimates describe correlation we do not interpret them causally: the specification conditions on variety choice, which is endogenous, and which for example implies seller, and hence seller size.

Data patterns II: product choice The relationship between project location and product choice is illustrated in Figure 1. The first two maps respectively give the locations of the plants and projects in the data. The third shows projects that use



(a) Plants (○–Sussex, ●–others) (b) Deliveries (all plants) (c) Deliveries (Sussex plants)

Map (a) shows plant locations, including the four (far-south) Sussex plants in hollow circles, map (b) shows all deliveries 2003-2006, and map (c) shows the subset of these deliveries from the Sussex plants.

Figure 1: Plant and delivery locations

varieties produced in four plants in Sussex, identified by (the far-south) hollow circles in the left-hand map: these projects have lower mean distances from the four identified plants, although in many cases buyers could have used a more closely-located plant.[12] In a similar vein, Panel A1 of Table 3 presents the proportion of buyers that select a product from the nearest x plants, for $x = (1, 5)$: buyers do not exclusively select the nearest plant, but do so more often than if they randomly selected one of the 36 plants. The second row of A1 shows that a buyer does not exclusively select the nearest plant of the chosen manufacturer, suggesting there is differentiation at product level rather than (or in addition to) firm level. Whilst the Euclidean distances we use do not fully measure transport cost—e.g. grid references may be inaccurate, roads are not straight-lines, and they do not account for congestion—the mean distance difference between the nearest and the chosen plant reported in panel A2 is large and unlikely to be entirely attributable to measurement factors. In sum, spatial differentiation is important but does not dominate the other factors that drive choices.

To explore variables related to product choice, Panel B shows parameter estimates for a simple choice model where we condition on choice of an inside good. We assume

[12] Although not obvious from the map, the distribution of plants and projects yields a *positive* correlation (across projects) between the distances to the nearest plant for any pair of manufacturers—i.e. if a project is located relatively close to one manufacturer, then it tends to be relatively close to each of the others. This contrasts with Hotelling where the correlation is -1.

A: Product choice				
A1: Proportion of choices in nearest $x \in \{1, 5\}$ plants to the project			x=1	x=5
All manufacturers (36 plants) [Comparison: $1/36 = 0.028$, $5/36 = 0.140$]			0.119	0.401
Chosen manufacturer			0.243	0.726
A2: Comparison of chosen and nearest product			Mean	SD
Extra distance of chosen relative to nearest product (km)			56.017	63.106
B: Estimated parameters for descriptive logit product choice model				
	(i)		(ii)	
Product characteristics (x_j)				
Color: red	0.235	(0.021)		
Shaping method: wire-cut	0.407	(0.028)		
Strength	−0.026	(0.004)		
Absorption	0.015	(0.007)		
ln (#varieties in product j)	0.713	(0.013)		
Buyer-product characteristics (y_{ij})				
Distance from buyer (DST_{ij}) 100km	−1.168	(0.036)	−1.357	(0.039)
Square of distance from buyer (DST_{ij})	−0.007	(0.011)	0.017	(0.012)
Buyer frost × strength	0.379	(0.084)	1.032	(0.108)
Buyer rainfall × absorb	−1.048	(0.300)	−0.709	(0.355)
Log likelihood	−48202.6		−48202.6	
Product dummies (β_j)	No		Yes	

Notes: The number of observations is 13,788. Standard errors in parentheses.

Table 3: Analysis of product choice

the payoff from product j in project i is $u_{ij} = \beta' x_j + \gamma' y_{ij} + \varepsilon_{ij}$ where x_j is a vector of j's non-price characteristics, y_{ij} is a vector of interactions between i and j, and ε_{ij} is an iid Type-1 EV effect (e.g. unobserved transport costs or local tastes). Included in x_j is the log of the number of varieties in j.[13] In specification (i) parameters β are significant, but, since price is not included, we do not have strong priors as to their sign; in (ii) we replace $\beta' x_j$ with unreported product dummies β_j which absorb the mean effects of product characteristics. The signs of the parameters γ in both specifications are as expected and mostly significant: distance has an overall negative effect, while synergies between rainfall and absorption, and frost and strength, are negative and positive respectively. A limitation with this specification is that prices are omitted because they are individualized and hence observed only for the chosen product; we now develop a model that allows us to account for the presence of unobserved prices.

[13] The log term accounts for unobserved variety-level product differentiation nested within product j (see Ackerberg and Rysman (2005)); this is absorbed into the product dummy in specification (ii).

3 The model

3.1 Players, products, and surplus from trade

Each buyer has a number of independent construction projects. For each project, the buyer selects a product $j \in \mathcal{J} = \mathcal{J}_J \cup \{0\}$ where $\mathcal{J}_J$ is the set of inside goods (i.e. brick products) and $j = 0$ is the outside good (i.e. non brick cladding). Each product has a distinct manufacturer. Let $\mathcal{K}$ be the set of manufacturers. The set of inside products is $\mathcal{J}_J = \cup_{k \in \mathcal{K}} \mathcal{J}_k$ where $\mathcal{J}_k$ is manufacturer k's portfolio. A project has a fixed quantity requirement and a specific location.[14] It is convenient to work in per-unit terms, so, utility, cost, surplus, prices, etc., are defined per unit of the quantity required in project i. Product j in project i gives the buyer money-metric utility v_{ij} (net of transport costs, which are paid for by the buyer). The manufacturer's cost of supplying the project is c_{ij}. The surplus is $w_{ij} = v_{ij} - c_{ij}$. The surplus from the outside good is w_{i0}. We assume that agents have complete information, and motivate this in section 3.3.

For a given project we use the surplus w_{ij} to define two key products, namely the first-best and the runner-up. For project i, the *first-best* product $j(i, 1)$ is defined as the highest-surplus product among all in $\mathcal{J}$, i.e.

$$j(i,1) = \underset{j \in \mathcal{J}}{\arg\max}\ w_{ij} \tag{1}$$

The first-best manufacturer $k(i, 1)$ produces this product. The *runner-up* product $j(i, 2)$ has the highest surplus among products sold by the first-best manufacturer's rivals, i.e.

$$j(i,2) = \underset{j \in \mathcal{J} \setminus \mathcal{J}_{k(i,1)}}{\arg\max}\ w_{ij}. \tag{2}$$

The runner-up manufacturer $k(i, 2) \in \mathcal{K} \setminus k(i, 1)$ produces the runner-up product. We refer to the difference between the surplus from the first-best and runner-up products as the first-best's *surplus advantage* and denote it $\Delta w_i = w_{ij(i,1)} - w_{ij(i,2)}$.

3.2 Equilibrium markups and product choice

In this subsection we consider the bargaining model for a given project, and to simplify notation we suppress i subscripts. Appendix A provides derivations of the results. The model comprises three parts: (i) a discrete-choice problem, in which the buyer selects from first-best and runner-up products, taking as given their negotiated markups, (ii)

[14] We assume the location and quantity requirements of a project are exogenous. In practice they are determined when the land is acquired, before the choice of cladding material is made.

two bilateral bargaining problems which determine the markups for the first-best and runner-up products respectively, taking as given the markup anticipated in the other problem, and (iii) an equilibrium concept to account for the two bargaining problems being interdependent.

Product choice given negotiated markups It is convenient to work in terms of markups, ρ_j, defined as price minus cost, i.e. $\rho_j \equiv p_j - c_j$ where p_j is the price of product j. Given that the markup ρ_j is the part of surplus w_j appropriated by the manufacturer, the rest is enjoyed by the buyer as indirect utility, i.e. $v_j - p_j \equiv w_j - \rho_j$. Given the markup pair $\rho = [\rho_{j(n)}]_{n\in\{1,2\}}$ the buyer chooses the product $j \in \{j(1), j(2)\}$ that generates the highest indirect utility $w_j - \rho_j$. The indicator function for the choice of product $j \in \{j(1), j(2)\}$, given markups ρ, is therefore

$$d_{j(n)}(\rho) = 1[w_{j(n)} - \rho_{j(n)} \geq w_{j(n')} - \rho_{j(n')}] \text{ for } n \in \{1,2\},\ n' = \{1,2\} \setminus \{n\}. \quad (3)$$

If (3) is a tie we assume the buyer selects the first-best product $j(1)$: in this case, assuming non-negative runner-up markups, the first-best seller $k(1)$ is always able to reduce markup by an arbitrary amount without making a loss.

Bilateral bargaining: feasible payoffs We now describe the payoff pairs that it is feasible to agree in each bilateral bargaining problem, taking account of the markup in the other agreement, and the buyer's product choice problem. Bilateral negotiation $n \in \{1,2\}$, given markup $\rho_{j(n')}$ in the other bargaining problem $n' = \{1,2\} \setminus \{n\}$, has the following set of feasible payoffs to the buyer and manufacturer respectively

$$\left\{\textstyle\sum_{n\in\{1,2\}} d_{j(n)}(\rho^*, \rho_{j(n')}) \times [w_{j(n)} - \rho_{j(n)}],\ d_{j(n)}(\rho^*, \rho_{j(n')}) \times \rho^* \mid \rho^* \in [0, w_{j(n)}]\right\}. \quad (4)$$

We assume that the agreed markup must be in the range $\rho^* \in [0, w_{j(n)}]$ to rule out equilibria in which a markup is either negative or greater than the surplus from trade. If the buyer is unable to conclude negotiations with either manufacturer—a situation known by bargaining theorists as the *impasse* point (see Binmore et al. (1989))—the buyer uses the outside good $j = 0$ and fully appropriates the surplus w_0.[15]

[15] We have written the notation for the case that the outside good is not either the first-best or the runner-up product. This is not assumed in the model. If the outside good is the first-best then the buyer selects the outside good and receives utility $w_{j(0)}$ without any negotiation, and if the outside good is the runner-up then $w_{j(2)} = w_0$. (In the latter case the alternative bargaining specification, discussed below, coincides with the baseline bargaining specification.)

TIOLI model The TIOLI model is an important reference point. In the TIOLI model each manufacturer posts a markup and the buyer selects the seller offering most utility. The best reply of manufacturer $k(n)$ in negotiation $n \in \{1,2\}$ to markup $\rho_{j(n')} \in [0, w_{j(n')}]$ in the other bilateral negotiation $n' = \{1,2\} \setminus \{n\}$ is

$$\rho^N_{j(n)}(\rho_{j(n')}) = \underset{\rho^* \in [0, w_{j(n)}]}{\operatorname{argmax}} \, d_{j(n)}(\rho^*, \rho_{j(n')}) \times \rho^*. \tag{5}$$

The choice condition in (3) tells us that to induce the choice of product $j(n)$ the markups must satisfy the inequality $\rho_{j(n)} < \rho_{j(n')} + w_{j(n)} - w_{j(n')}$. Using standard Bertrand-Nash reasoning, in which the best-reply is the markup that marginally attracts the buyer (subject to the markup being non-negative), the best reply (5) can be written

$$\rho^N_{j(n)}(\rho_{j(n')}) = \max[0, \rho_{j(n')} + w_{j(n)} - w_{j(n')} - \iota_n], \text{ for } n \in \{1,2\}, \; n' = \{1,2\} \setminus \{n\}, \tag{6}$$

where ι_2 is small and positive and $\iota_1 = 0$ (since we assume the buyer selects first-best in a tie). The two best reply functions in (6) are mutually consistent only when the first-best and runner-up markups are equal to the surplus advantage and zero respectively:

$$\rho_{j(n)} = \begin{cases} \Delta w & \text{for } n = 1 \\ 0 & \text{for } n = 2. \end{cases} \tag{7}$$

The buyer chooses the first-best product and, since the choice is marginal, gets a payoff equal to the runner-up product's surplus $w_{j(2)}$. This result is familiar from models of individualized Bertrand-Nash price setting (e.g. Thisse and Vives (1988)).

Bargaining model In the bargaining model, unlike the TIOLI model, the buyer has bargaining power in each bilateral negotiation. We model each bilateral negotiation using a Nash bargaining model in which the disagreement point is the impasse point, where the buyer buys the outside good and gets surplus w_0. The buyer also has what bargaining theorists call an outside option, which constrains negotiations. The outside option is to buy the product in the other bilateral negotiation at its anticipated markup. To solve the model we begin by deriving the Nash bargaining solution in which the outside option is absent, which, in negotiation $n \in \{1,2\}$, is given by

$$\rho^A_{j(n)} = \underset{\rho^* \in [0, w_{j(n)}]}{\operatorname{argmax}} \, [w_{j(n)} - \rho^* - w_0]^{b_i} \times [\rho^* - 0]^{b_{k(n)}} \quad = b_{ik(n)}(w_{j(n)} - w_0) \tag{8}$$

where $b_i \geq 0$ and $b_{k(n)} \geq 0$ represent the bargaining skill of the buyer and manufacturer respectively and $b_{ik(n)} = b_{k(n)}/(b_i + b_{k(n)})$ is a bargaining parameter representing the manufacturer's relative bargaining strength.

The buyer's outside option in negotiation $n \in \{1, 2\}$ is to buy the product in the other negotiation $n' = \{1, 2\} \setminus \{n\}$ at its anticipated markup $\rho_{j(n')}$. This option is relevant only if it induces her to switch away at the Nash bargaining solution $\rho^A_{j(n)}$. This is the case if $\rho^A_{j(n)}$ exceeds the best reply function $\rho^N_{j(n)}(\rho_{j(n')})$ defined in (6). Hence, the markup that solves the bilateral bargaining problem can be written

$$\rho^B_{j(n)}(\rho_{j(n')}) = \min\left[\rho^A_{j(n)},\ \rho^N_{j(n)}(\rho_{j(n')})\right], \tag{9}$$

or, more explicitly, substituting from (8) and (6),

$$\rho^B_{j(n)}(\rho_{j(n')}) = \min\left[b_{ik(n)}(w_{j(n)} - w_0), \max[0, \rho_{j(n')} + (w_{j(n)} - w_{j(n')}) - \iota_n]\right]. \tag{10}$$

This approach applies the outside option principle introduced in Binmore et al. (1989) which says that an outside option has no effect on a Nash bargaining problem unless it constrains it. The principle is based on the argument that any threat to use the outside option is not credible unless doing so leaves the buyer better off. Unlike Binmore et al. (1989), which considers a single bilateral problem and an exogenous outside option, we study two bilateral problems, where the outside option in one problem is endogenous and determined in the other bilateral negotiation. It is the outside option that generates the interdependence between negotiations.

To solve for an equilibrium we assume that the two bilateral bargaining problems are mutually consistent—i.e the markup for each bilateral problem solves that problem given the markup in the other bilateral problem. In the unique equilibrium outcome the first-best markup is the minimum of the Nash bargaining solution and the TIOLI markup and the runner-up markup is zero, i.e.

$$\rho_{j(n)} = \begin{cases} \min\ [b_{ij(1)}(w_{j(1)} - w_0), \Delta w] & \text{for } n = 1 \\ 0 & \text{for } n = 2 \end{cases} \tag{11}$$

and the buyer selects the runner-up product. See Appendix A for a derivation.[16,17]

[16]Manufacturer bargaining skill does not affect buyer's choice of product: the payoff of the buyer when selecting $j(1)$ is never lower than $w_{j(2)}$ even when $b_{ij(1)} = 1$ as the first-best manufacturer must offer at least the payoff the buyer can get when buying $j(2)$ at marginal cost.

[17]As a consequence of inducing the buyer to choose the first-best product, we show in Appendix A that the equilibrium has the property that it is "bilaterally efficient" in each negotiation—i.e. in each negotiation the agreed markups maximize the sum of the payoffs of the two negotiating agents

At the equilibrium markups the negotiation with the runner-up is always constrained by the outside option of buying the first-best product. The negotiation with the first-best is however constrained by the outside option of buying the runner-up product only if the first-best manufacturer's markup is greater in the Nash bargaining solution than in the TIOLI solution (i.e. $b_{ij(1)}(w_{j(1)} - w_0) > \Delta w$). Only in this case does the buyer benefit from competition, because the first-best manufacturer must reduce its markup to Δw to retain the buyer. Note that as the bargaining parameter increases (and the buyer becomes weaker) this is more likely to happen. In the limiting case, where $b_{ij(1)} = 1$, it always does, because the first-best product's surplus advantage $\Delta w = (w_{j(1)} - w_{j(2)})$ is by definition less than its surplus difference with the outside good $(w_{j(1)} - w_0)$. Hence, the bargaining model nests the TIOLI model for the case where $b_{ij(1)} = 1$.

The model is an equilibrium of a pair of bilateral Nash bargaining problems in which the buyer has the outcome from the other problem as an outside option. Given that the model is derived using interacting axiomatic bargaining models, rather than from non-cooperative game theory, it is useful to discuss how we interpret it. As we discuss next, the model has microfoundations in a number of noncooperative bargaining models with multiple rival sellers and discrete buyer choice. Thus we can interpret our model as a representation of equilibrium in a noncooperative bargaining model.[18]

Noncooperative microfoundations The outcome of the bargaining model (11) is supported in a number of alternative noncooperative bargaining models where the buyer negotiates with multiple sellers (and the buyer must select no more than one).[19] In these models the outcomes are obtained in the limiting equilibrium as time discounting goes to zero in the non-cooperative framework that dates back to Rubinstein (1982). All the models assume single-sourcing buyers, all have sellers that differ in terms of how much surplus they generate in trade with that buyer, and all have the desirable feature that

(accounting for product choice) given the markups agreed in the other bilateral negotiation—which is the definition of a contracts equilibrium given in Cremer and Riordan (1987).

[18] Turning to cooperative game theory, we note that the model's outcome is in the *core* of the coalition game involving all three parties (namely the buyer and the two manufacturers)—i.e. it satisfies the following principles that we may *a priori* consider reasonable: it (i) maximizes and fully distributes the total surplus, (ii) ensures that no sub-coalition of the parties can be made better off without another being made worse off, and (iii) implies a zero allocation of surplus to players that contribute nothing to the overall surplus (namely the runner-up and other rivals). Moreover, each possible allocation in the core can be achieved for some value of the relative bargaining skill b_{ij} in its range $[0, 1]$, and this parameter can be seen as capturing how the parties split the surplus. Hence, the model can also be interpreted as representing an equilibrium that satisfies these principles, without assuming a specific non-cooperative model.

[19] In the literature referenced in this paragraph, some papers present the problem with a single seller negotiating with multiple buyers and others with a single buyer negotiating with multiple sellers. The strategic problem is formally equivalent in these two alternative cases. We summarize all papers as though they were for a single buyer and multiple sellers, consistent with our setting.

they allow information flow between the negotiations for the two alternative goods.[20] The models differ in the timing of offers and the identity of who makes an offer at each stage, but all generate the markup and choice outcome in our model as the equilibrium. The first model is the seminal one-buyer two-seller "auctioning model" which is sketched in Binmore (1985) and Binmore et al. (1992) (and derived formally in Chapter 9.3 of Osborne and Rubenstein (1990)). This has an alternating-offer protocol in which the buyer begins by announcing a number, which represents the net utility she requires if agreement is to be reached, which both sellers hear. If the first-best seller accepts then there is trade but if he rejects then the runner-up can decide whether to accept or to reject. If both reject there is a delay before the two sellers make simultaneous offers to the buyer and the buyer can select one to accept. If the buyer rejects both then there is another delay before the buyer can offer again. A closely related model which gives the same equilibrium outcome but with a slightly different sequence of moves is the "non-integration" case in Bolton and Whinston (1993). Another is the (no-intermediary version of the) model in Manea (2018) which differs from the others in this paragraph by adopting a "random-proposer" protocol, in which the buyer selects in any period an upstream seller $k \in \mathcal{K}$ and with probability $\varpi \in (0,1)$ the buyer proposes a price and seller k decides whether to accept and roles are reversed with probability $(1-\varpi)$. In either event if the offer is rejected the game proceeds to the next period and the process is repeated, and so on.[21] Finally, the Appendix in Ghili (2018) presents a further model which generates the outcomes in our model. This has an alternating-offer protocol where the timing of moves between the buyer and sellers is as described in Collard-Wexler et al. (2019) but in a set-up where the payoffs (unlike those in Nash-in-Nash) are such that buyer prefers single-sourcing.

Alternative bargaining model Binmore et al. (1989) note the possibility that in applied work there is more than one plausible specification for the disagreement point. An alternative to the (baseline) bargaining model is to assume that in each bilateral negotiation $n \in \{1,2\}$ the disagreement point is to buy the other product $j(n')$ at the markup agreed in the other negotiation, so the disagreement payoff is $(w_{j(n')} - \rho_{j(n')})$.

[20] The last of these features is absent from an alternative approach to establishing non-cooperative foundations for multilateral bargaining models, which uses an "independent agents" representation, in which the buyer sends a separate agent to each seller, and each negotiation proceeds bilaterally with alternating offers and no information flow between the negotiations (see Chipty and Snyder (1999)). It is possible to microfound the baseline bargaining model in this alternative approach, assuming that (i) time discounting derives from from time preference (see Binmore et al. (1986), *deal-me-out* case) and (ii) a zero markup is anticipated for the runner up good.

[21] This protocol is adapted by Ho and Lee (2019) to allow for situations where the buyer benefits from trading with multiple manufacturers in equilibrium; this is a generalization which we do not require given that in our framework the buyer single-sources.

The outcome of the model is

$$[\rho_{j(1)}, \rho_{j(2)}] = [b_{ij(1)}(w_{j(1)} - w_{j(2)}), 0]. \tag{12}$$

The first-best markup is lower than in the TIOLI outcome and the buyer buys the first-best good. In the negotiation with the first-best, the first-best markup in (12) is the Nash Bargaining solution, since the gains from trade with the first-best are $w_{j(1)} - w_{j(2)}$ when the runner up has a zero markup. The negotiation with the runner-up does not have a well defined Nash bargaining solution, since the gains from trade with the runner-up are negative when the first-best markup is less than the TIOLI price, so instead it is assumed that the buyer and runner-up agree a zero markup given they do not expect to trade. This alternative model is discussed in Miller (2014). The alternative model (like the baseline) nests the TIOLI case when $b_{ij(1)} = 1$. It does not appear to be as strongly micro-founded in the non-cooperative bargaining literature as the baseline model.[22] For this reason we proceed with the baseline bargaining model in the rest of the paper. However, as a check on robustness, we also estimate and present results from the alternative specification.[23]

3.3 Specification of value, cost and bargaining skill

We now reintroduce i subscripts to specify how value v_{ij}, cost c_{ij}, and the bargaining parameter b_{ij}, vary across projects. The variation in surplus $w_{ij} = v_{ij} - c_{ij}$ follows.

The value in project i of product j is

$$v_{ij} = \delta_j + \beta' z_{ij}^{(1)} - \alpha' z_{ij}^{(2)} + \varepsilon_{ij} \tag{13}$$

where δ_j is a constant effect for the product and the remaining terms capture the project-product match. $z_{ij} = (z_{ij}^{(1)}, z_{ij}^{(2)})$ is a vector of value-shifters available to the econometrician. We divide z_{ij} into two parts: $z_{ij}^{(1)}$ shifts value (up to transport costs) and $z_{ij}^{(2)}$ shifts transport costs. $z_{ij}^{(1)}$ includes (i) interactions of dummies for project region and aesthetic product characteristics (to pick up regional variation in aesthetic tastes)[24] and dummies for whether the product is produced in the same area as the

[22] We are unaware of any micro-foundation for the alternative model in non-cooperative bargaining theory with multiple sellers other than in the "independent agents" representation described in footnote 20, where its predictions for the first-best markup can be derived assuming that (i) time discounting derives from from an exogenous probability of breakdown at each stage (see Binmore et al. (1986), *split-the-difference* case) and (ii) a zero markup is anticipated for the runner up good.

[23] In Appendix A we derive the first-best markup in (12) and the associated likelihood function.

[24] For parsimony we use two large regions, north and south, to interact with aesthetic characteristics. The south region is NUTS1 regions H-K and the north region is other NUTS1 regions. This partition of

project (to pick up a "home" taste effect);[25] (ii) interactions of weather conditions for project region and technical characteristics of the product; and (iii) pairwise buyer-manufacturer indicators (to capture buyer-specific preferences over manufacturers).[26] $z_{ij}^{(2)}$ includes fuel costs and straight-line distance to the project from the production location. ε_{ij} captures heterogeneity in the project-product match that is not measured by the econometrician in z_{ij} because (e.g.) the spatial granularity of the regional taste and weather variables is quite crude, because there are omitted brick characteristics, or because straight-line distance leaves measurement error in transport costs. We assume ε_{ij} is iid across projects i according to a GEV distribution (nesting the inside goods) with parameters $\sigma = (\sigma_J, \sigma_\varepsilon)$, where $\sigma_J \in [0, 1]$ is the nesting and σ_ε the scale parameter.[27]

The (unit) cost of supplying project i with quantity q_i of product j is

$$c_{ij} = \gamma' \mathrm{w}_{ij}^c + \gamma_f / q_i + \sigma_\nu \nu_i. \tag{14}$$

The vector w_{ij}^c is cost-shifters including input prices, a dummy for product j's plant, and an indicator for whether product j is low quality.[28] γ_f is a fixed cost which allows transaction-level scale effects. Finally, ν_i is iid across projects with a standard normal distribution and allows projects to vary in supply cost—e.g. production timing requirements within the year or bespoke shape requirements specified by the buyer.

A number of features of the model motivate the simplifying assumption of complete information about values (13) and costs (14). First, manufacturers and buyers are few and trade repeatedly. Second, there is little process or product innovation. Third, factors affecting the project-product match, including those not observed by the econometrician, tend to be quite transparent and largely driven by project location—e.g. (i) the tastes of the final house-buying public to whom housing is marketed, (ii) local environmental and weather considerations, and (iii) the overall cost of transport from the production location—and manufacturers are likely to become familiar with these from

GB reflects what is said on regional preference in CC (2007) paragraph 5.26: "soft mud [molded] bricks were, we were told, predominantly used in the South, and extruded [wirecut] bricks in the Midlands and North." Our estimates in the next section are consistent with this pattern.

[25] The CC report, CC (2007), mentions this effect in paragraph 5.26, where they say that there is evidence of distinct regional brick preferences which "seemed to be driven by historical factors, particularly customer preferences for bricks which historically had been produced locally."

[26] Buyer-specific preferences over manufacturers are motivated in CC (2007) (paragraph 4.71): buyers consider quality factors that vary by manufacturer such as continuity of supply, consistent quality, complementary services, quality of just-in-time production and after-sales service.

[27] Given the inclusion of the δ_j terms, the specification is consistent with a choice between varieties (nested) within each j; this follows from the maximum stability property of the GEV distribution (see Ackerberg and Rysman (2005) and footnote 13).

[28] A low quality product is defined as one with a below-median (across $j \in \mathcal{J}$) ratio of strength to water absorption. Low quality bricks have a lower energy requirement in the production process.

repeated market activity in multiple locations.

We assume that the bargaining skill is determined at the level of the manufacturer and buyer. Let $h(i)$ and $k(j)$ denote the buyer for project i and manufacturer of product j respectively. The bargaining skill of agent l (a buyer or manufacturer) is $b_l = \exp(\eta_1 1_{[l \in \mathcal{K}]} + \eta_2 y_l)$ where $\eta = (\eta_1, \eta_2)$ are parameters, $1_{[l \in \mathcal{K}]} \in \{0, 1\}$ indicates whether the agent l is a manufacturer, and y_l is agent size, defined as the log of l's number of transactions in the 4-year period of the data. A manufacturer with size difference $y_{ij} = y_{k(j)} - y_{h(i)}$ has relative bargaining power

$$b_{ij} = b_{k(j)}/(b_{k(j)} + b_{h(i)}) = \exp(\eta_1 + \eta_2 y_{ij})/(1 + \exp(\eta_1 + \eta_2 y_{ij})) \in [0, 1].$$

Conditional on the primitives of the model, the specification implies that choice and price outcomes in a given project are independent of those in other projects. This rules out at least three potential forms of non-independence. First, intra-manufacturer effects generated by plant-level capacity constraints; we regard these as negligible in our application, given that plants are not operating close to capacity, have high levels of inventory, and have a large capacity relative to individual transactions (see CC (2007) para 7.8).[29] Second, inter-buyer interdependence could arise because buyers compete in the retail market for new houses; however, in our framework bargaining induces the efficient buyer choice, so negotiations over price transfer bilateral surplus without impacting the buyer's retail price or output decisions. Third, consider intra-buyer interdependence. Given that the projects are spatially separate there is no obvious role for intrinsic taste synergies. There is also little role for synergies arising from shopping costs—i.e. costs per manufacturer used across all transactions in any buying period: buyers are already multi-sourcing (in different transactions) and according to CC (2007) (paragraph 7.7) face no significant switching costs. Moreover while, with non-individualized pricing, multi-product firms may have bundling incentives—loosely, cutting price on one product to attract a buyer to another—these do not arise when prices are individualized, with or without shopping costs, since negotiated prices induce the buyer to choose the first-best product separately in each transaction.[30]

[29] The framework we use permits a relaxation of this where buyers and sellers condition on the equilibrium outcomes of negotiations in other projects (the approach in Chipty and Snyder (1999)), e.g. let costs to k from project i be $c_k(q_i, Q_{-i})$ where Q_{-i} is a vector of quantities in other projects, and assume Q_{-i} is unaffected by the bargaining process for i.

[30] As Nalebuff (2009) points out, while a seller in a market with non-individualized pricing might sell a bundle of complementary items at a discount relative to its individual items, the presence of such discounts "depends on an unstated assumption: that firms set a single price in the market to all customers. This is a quite reasonable assumption for a typical consumer good, such as Microsoft Office. But it is not a reasonable assumption for the sale of large commercial products in which the two parties engage in extensive negotiation as part of the sale process. If firms can price discriminate or negotiate

4 Probability, likelihood and estimation

For each project using an inside good the transactions data records: (i) the first-best product and its negotiated price, $[j(i,1), p_i]$, (ii) shifters of joint surplus $x_i = [x_{ij}]_{j \in \mathcal{J}_J}$ where $x_{ij} = (z_{ij}^{(1)}, z_{ij}^{(2)}, \mathrm{w}_{ij}^c, q_i)$, and (iii) shifters of the first-best manufacturer's bargaining skill relative to the buyer $y_{ij(i,1)}$. We also observe, using other sources, the market share s_{0m} of the outside good, and hence the number of projects N_{0m} choosing it, for each region-year market $m \in \mathcal{M}$. There are two main econometric challenges. First, for any project i, we do not observe the buyer's runner-up good or the prices the buyer would have paid for products she did not choose (unlike standard choice models, e.g. Berry et al. (1995)). Second, there is a selection issue in the pricing equation, similar to that in Dubin and McFadden (1984): the choice of product and the individualized price both depend on unobserved shocks (ν_i, ε_i), so that, conditional on product choice, variables in the price equation are endogenous. To address these challenges we estimate the pricing and choice parts of the model jointly. To do this we use the model to predict the runner-up product and its impact on the first-best price, given the unobservables, and then integrate out the unobservables. There are many candidate runner-up products, so this is a high-dimensional integration problem; we show that when idiosyncratic tastes are GEV there is a tractable likelihood for the joint probability of the observed choice and price. A separate challenge is that the transactions data do not include transactions for the outside good, which is why we add data on its market share by region-year.

4.1 Probability expressions

Inequality conditions for choice and first-best markup In this section we derive a set of inequalities that are necessary and sufficient conditions for buyer i to choose product j at a markup ρ_{ij} that exceeds some constant $\rho > 0$. To do this we combine a set of inequalities for choice of product j with a second set of inequalities for its markup to exceed ρ. We obtain the former set of inequalities from the property that equilibrium markups induce choice of the first-best product, so that in equilibrium

$$(i \text{ chooses } j) \quad \Longleftrightarrow \quad w_{ij} \geq w_{ij'} \quad \forall j' \in \mathcal{J}. \tag{15}$$

We obtain the latter set of inequalities from the equilibrium first-best markup in (11)

$$\rho_{ij} = \min[b_{ij}(w_{ij} - w_0), \Delta w_i] \tag{16}$$

with each customer, then the advantage to bundling disappears."

which says the markup is the minimum of the Nash bargaining solution and the surplus advantage over the runner-up good. The definition of the runner-up good (see (2)) implies it has the lowest surplus advantage among rival manufacturer's goods, i.e.

$$\Delta w_i = \min(w_{ij} - w_{ij'})_{j' \in \mathcal{J}_J \setminus \mathcal{J}_{k(j)}} \tag{17}$$

where j is the first-best good. Hence, substituting (17) into (16) the markup must be less than or equal to the Nash bargaining solution and every surplus difference with a rival manufacturer's good:

$$\rho_{ij} = \min[b_{ij}(w_{ij} - w_{i0}), (w_{ij} - w_{ij'})_{j' \in \mathcal{J}_J \setminus \mathcal{J}_{k(j)}}]. \tag{18}$$

It follows from the conditions in (18) that if the markup is greater than or equal to a positive constant ρ then so must be the Nash bargaining markup and the surplus difference with each rival manufacturer's good, i.e.

$$\rho_{ij} \geq \rho \iff [b_{ij}(w_{ij} - w_{i0}), (w_{ij} - w_{ij'})_{j' \in \mathcal{J}_J \setminus \mathcal{J}_{k(j)}}] \geq \rho \tag{19}$$

or, rearranging

$$(\rho_{ij} \geq \rho) \iff \begin{cases} w_{ij} \geq \rho / b_{ij} + w_{ij'} & \text{for } j' = 0 \\ w_{ij} \geq \rho + w_{ij'} & \forall j' \in \mathcal{J}_J \setminus \mathcal{J}_{k(j)}. \end{cases} \tag{20}$$

The necessary and sufficient conditions for the *joint* outcome in which i chooses j and pays a markup greater than ρ are given by combining the choice conditions in (15) and the pricing conditions in (20). Notice that, for $\rho > 0$, the condition in (20) for a given j' implies the condition for the same j' in (15), i.e. the inequalities in (20) are sufficient for the corresponding ones in (15). Thus, pooling (15) and (20), we get

$$(i \text{ chooses } j \text{ and } \rho_{ij} \geq \rho) \iff \begin{cases} w_{ij} > w_{ij'} & \forall j' \in \mathcal{J}_{k(j)} \\ w_{ij} > \rho / b_{ij} + w_{ij'} & \text{for } j' = 0 \\ w_{ij} > \rho + w_{ij'} & \forall j' \in \mathcal{J}_J \setminus \mathcal{J}_{k(j)}. \end{cases} \tag{21}$$

Choice probabilities Since the conditions in (21) are in the same form as the inequalities of a standard discrete-choice model, we can leverage results from discrete-choice theory, developed for example in McFadden (1978), to compute probability measures. To derive probabilities we write $w_{ij} = \omega(x_{ij}, \nu_i) + \varepsilon_{ij}$, defining $\omega(x_{ij}, \nu_i)$ as surplus up to ε_{ij} given project type (x_i, ν_i). Following standard practice we normalize surplus levels such that $w_{i0} = \varepsilon_{i0}$ for the outside good. Let the vector $\varepsilon_i = (\varepsilon_{ij})_{j \in \mathcal{J}}$ have the probability distribution function G_ε. The probability s_{ij} that product $j \in \mathcal{J}_J$ is chosen for project i of type (x_i, ν_i) is is the probability that ε_i satisfies the inequalities in (15):

$$s_{ij} = \int_{\varepsilon_i} 1\{\omega_{ij} + \varepsilon_{ij} \geq \max[(\omega_{ij'} + \varepsilon_{ij'})_{j' \in \mathcal{J}_J}, \varepsilon_{i0}]\} dG_\varepsilon(\varepsilon_i) \tag{22}$$

where $\omega_{ij} = \omega(x_{ij}, \nu_i)$. Since $\varepsilon_i \sim$ GEV (where inside goods are nested with parameter σ_J), we have from McFadden (1978) that $s_{ij}(x_{ij}, \nu_i) = s_{ij|J}(x_{ij}, \nu_i) s_{iJ}(x_{ij}, \nu_i)$ where

$$s_{ij|J}(x_{ij}, \nu_i) = \frac{\exp\{\frac{\sigma_\varepsilon}{\sigma_J}\omega_{ij}\}}{\sum_{j' \in \mathcal{J}_J} \exp\{\frac{\sigma_\varepsilon}{\sigma_J}\omega_{ij'}\}}, \;\; s_{iJ} = \frac{\exp\{\sigma_J W_i\}}{1 + \exp\{\sigma_J W_i\}}$$

and $W_i = \ln[\Sigma_{j' \in \mathcal{J}_J} \exp\{\frac{\sigma_\varepsilon}{\sigma_J}\omega_{ij'}\}]$.

Joint probability measure for choice and markup To derive the discrete-continuous probability measure for buyer i's choice and markup outcome we rewrite the inequalities (21) as follows

$$\begin{aligned} &(i \text{ chooses } j \text{ and } \rho_{ij} \geq \rho) \\ \iff & \omega_{ij} + \varepsilon_{ij} \geq \omega_{ij'} + \varepsilon_{ij'} + \rho \times (\chi_{jj'} + b_{ij}^{-1} 1_{[j'=0]}) \quad \forall j' \in \mathcal{J} \end{aligned} \tag{23}$$

where $\chi_{jj'} = 1_{[j' \in \mathcal{J}_J \setminus \mathcal{J}_{k(j)}]}$ indicates whether j' is a rival manufacturer's good. The probability $r_{ij}(\rho)$ that product j is chosen and that its markup *exceeds* ρ for a project of type (x_i, ν_i) with bargaining skill shifters y_{ij} is the probability that ε_i satisfies the inequalities in (23), i.e.

$$\begin{aligned} r_{ij}(\rho) =& \Pr(i \text{ chooses } j \text{ and } \rho_{ij} \geq \rho | x_i, y_{ij}, \nu_i) \\ =& \int_{\varepsilon_i} 1\{\omega_{ij} + \varepsilon_{ij} \geq \max[(\omega_{ij'} + \varepsilon_{ij'} + \rho\chi_{jj'})_{j' \in \mathcal{J}_J}, \rho b_{ij}^{-1} + \varepsilon_{i0}]\} dG_\varepsilon(\varepsilon_i). \end{aligned} \tag{24}$$

Since the inequalities in the second line of (24) have the same structure as those for the discrete choice problem in (22), it follows by analogy from McFadden (1978) that $r_{ij}(\rho) = r_{ij|J}(\rho) r_{iJ}(\rho)$ where

$$r_{ij|J}(\rho) = \frac{\exp\{\frac{\sigma_\varepsilon}{\sigma_J}\omega_{ij}\}}{\sum_{j' \in \mathcal{J}_J} \exp\{\frac{\sigma_\varepsilon}{\sigma_J}[\omega_{ij'} + \rho\chi_{jj'}]\}}, \quad r_{iJ}(\rho) = \frac{\exp\{\sigma_J R_i(\rho)\}}{\exp\{\sigma_\varepsilon \rho b_{ij}^{-1}\} + \exp\{\sigma_J R_i(\rho)\}} \tag{25}$$

and $R_i(\rho) = \ln(\Sigma_{j' \in \mathcal{J}_J} \exp\{\frac{\sigma_\varepsilon}{\sigma_J}[\omega_{ij'} + \rho\chi_{jj'}]\})$.

To obtain the discrete-continuous probability measure $f_{ij}(\rho)$ of observing choice j

at markup ρ for project i we differentiate $r_{ij}(\rho)$ in (24) with respect to ρ: $f_{ij}(\rho) = -\partial r_{ij}(\rho)/\partial\rho$. $f_{ij}(\rho)$ has a convenient closed form given in Proposition 1.

Proposition 1. If $\varepsilon_i \backsim$ GEV, nested by $\mathcal{J}_J$, with nesting parameter σ_J, then the discrete-continuous probability measure, of choice j at markup ρ for project i, is

$$f_{ij}(\rho) = -\frac{\partial r_{ij}(\rho)}{\partial \rho} = \sigma_\varepsilon r_{ij}(\rho)[1 - r_{ik}(\rho) - (1-\sigma_J^{-1})(1 - r_{ik|J}(\rho))] - (1 - b_{ij}^{-1})r_{ij}(\rho)r_{i0}(\rho)$$

where $r_{ik}(\rho) = \Sigma_{j\in\mathcal{J}_k} r_{ij}(\rho)$ and $r_{ik|J}(\rho) = \Sigma_{j\in\mathcal{J}_k} r_{ij|J}(\rho)$.

Proof. See Appendix A. □

To get the expressions in terms of observable data we begin by writing them in terms of project type (x_i, ν_i), where cost shock ν_i has standard normal distribution function $G_\nu(\nu_i)$. Thus we write the choice probability $s_{ij} = s_j(x_i, \nu_i)$ and the choice and markup probability measure $f_{ij}(\rho) = f_j(\rho|x_i, y_{ij}, \nu_i)$. Since we would like to express the likelihood in terms of price p (rather than the markup ρ, which is not observed) we define $f_{ij}^*(p|x_i, y_{ij}, \nu_i) = f_j(p - c_i(x_i, \nu_i)|x_i, y_{ij}, \nu_i)$. To obtain probability expressions in terms only of observable type we integrate out ν_i to obtain

$$s_j(x_i) = \int_{\nu_i} s_j(x_i, \nu_i) dG_\nu(\nu_i) \quad \text{and} \quad f_j^*(p|x_i, y_{ij}) = \int_{\nu_i} f_j^*(p|x_i, y_{ij}, \nu_i) dG_\nu(\nu_i) \qquad (26)$$

We obtain the integrals by simulation.[31]

The analytical forms $s_j(x_i, \nu_i)$ and $f_{ij}^*(p|x_i, y_{ij}, \nu_i)$ are derived using the GEV assumption and hence, conditional on any project's type (x_i, ν_i), they imply the substitution patterns of a nested logit model. However, the framework can accommodate additional unobserved random effects: as we have just seen, equation (26) integrates out a random cost effect. It is possible to add random utility parameters effects too, and integrate these out numerically, as done in the mixed logit approach in Berry et al. (1995). This might be desirable in some applications to allow more flexibility in substitution patterns. We do not include any random utility coefficients because in our application we

[31] In the integral for $f_j^*(p_i|x_i, y_i)$ in (26) we use importance sampling to avoid cost shocks ν_i that are uninformative because they imply negative markups, which have zero probability. Let ν_i^c be the highest cost shock consistent with non-negative markups, i.e., from costs (14), $\nu_i^c = (p_i - \gamma' \mathrm{w}_{ij}^c + \gamma_f/q_i)/\sigma_\nu$, which implies

$$f_j^*(p_i|x_i, y_{ij}) \;=\; \textstyle\int_{-\infty}^{\nu_i^c} f_j^*(p_i|x_i, y_{ij}, \nu_i) g_\nu(\nu_i) d\nu_i \;=\; G_\nu(\nu_i^c) \int_{-\infty}^{\nu_i^c} f_j^*(p_i|x_i, y_{ij}, \nu_i) \tilde{g}_\nu(\nu_i) d\nu_i. \quad (27)$$

The first equation follows because the likelihood is zero outside the limit of integration. In the second equation $\tilde{g}_\nu(\nu_i) = g_\nu(\nu_i)/G_\nu(\nu_i^c)$ is the density for the upper-truncated standard normal distribution, where $g_\nu(\nu_i)$ is the standard normal density. We simulate the integral for each i using 200 independent draws from $\tilde{g}_\nu(\nu_i)$ in the range $(-\infty, \nu_i^c)$.

include in the utility specification a detailed set of observed product-project interactions z_{ij} which capture taste heterogeneity between projects (see (13)).

The unconditional market share s_{mj} of product j, in arbitrary market m, is obtained by summing over (discrete) x-types, i.e. $s_{mj} = \Sigma_x s_j(x)\mu(x|m)$ where $\mu(x|m)$ is the proportion of projects in m that are of type x including those using the outside good.[32]

4.2 Likelihood function

Let $Y = \{[j(i,1), p_i, x_i, y_{ij(i,1)}]_{i\in\mathcal{I}_J}, (N_{0m})_{m\in\mathcal{M}}\}$ summarize the data where $\mathcal{I}_J$ is the set of projects using an inside good. Let the parameters be (θ,δ), where $\theta = (\beta,\alpha,\sigma,\gamma,\eta)$ and $\delta = (\delta_j)_{j\in\mathcal{J}_J}$. Rewriting probability expressions in terms of parameters (θ,δ) the function $f^*_{j(i,1)}(p_i,\theta,\delta|x_i,y_{ij(i,1)})$ is the joint probability measure of a project of type x_i selecting $j(i,1)$ at price p_i given bargaining skill shifters $y_{ij(i,1)}$, and the function $s_{m0}(\theta,\delta)$ is the probability that a project of unknown type in region-year market m selects the outside good. The log-likelihood function is given by

$$l(\theta,\delta,Y) = \Sigma_{i\in\mathcal{I}_J} \ln f^*_{j(i,1)}(p_i,\theta,\delta|x_i,y_{ij(i,1)}) + \Sigma_{m\in\mathcal{M}} N_{m0} \ln s_{m0}(\theta,\delta) \quad (28)$$

where the first term is the sum of the contributions from the $|\mathcal{I}_J|$ projects for which inside goods are chosen (for which we have transaction-level data) and the second is the sum of contributions from the $\Sigma_{m\in\mathcal{M}}N_{m0}$ projects in which the outside good is chosen (for which we observe the number of projects in each region-year market). Parameters are obtained by maximizing the likelihood. To reduce the dimension of the maximization problem we use an inversion method as used in Berry et al. (1995). We concentrate (28) with respect to the vector of mean utilities δ by inverting the market share functions $s_M(\theta,\delta) = [s_{Mj}(\theta,\delta)]_{j\in\mathcal{J}}$ where market M is Great Britain over the full 4-year period of the data. This gives a vector of mean utilities $\delta(\theta, s_M)$ for any candidate value of θ and observed market share vector s_M.[33] The parameters that maximize the log-likelihood

[32] For $\mu(x|m)$ we assume that projects are geographically distributed between NUTS2 sub-regions within m in proportion to official data on the number of new houses completed for the 4-year period of the data, and that x is distributed within any NUTS2 sub-region and year according to its empirical distribution in the transactions data. To be concrete let $m = (\kappa, t)$ where κ is a NUTS1 region and t is a year. Then $\mu(x|m) = \Sigma_{\tau\in\Omega_\kappa}\mu_1(x|\phi,t)\mu_2(\phi|\kappa)$ where ϕ indexes NUTS2 regions, Ω_κ is the set of NUTS2 regions in κ, $\mu_1(x|\phi,t)$ is the distribution of x in the transactions data for ϕ and t, and $\mu_2(\phi|\kappa)$ is the distribution of the number of new houses completed in the 4-year period of the data, from the Office for National Statistics *House Price Statistics for Small Areas*; since these data on completions are presented by dwelling size class we standardize by giving a detached house a weight of 1, a semi-detached house 0.75, a terraced house 0.5 and an apartment 0.40. There are 39 NUTS2 regions in Great Britain. We consider NUTS2 regions to be sufficiently granular that we do not need to distribute projects geographically within them using external data such as postal addresses

[33] To obtain $\delta(\theta, s_M)$ we follow Berry et al. (1995) and iterate the system $\delta^{\iota+1} = \delta^\iota + \ln[s_M] - \ln[s_M(\theta,\delta^\iota)]$ where ι is an iteration count. The jth element of s_M, i.e. the national market share for

function are given by $\hat{\theta} = \text{argmax}_\theta \; l(\theta, \delta(\theta, s_M), Y)$.

4.3 Informal discussion of identification

Identification differs in three ways from the standard discrete-choice setting with micro data discussed in Berry and Haile (2020). First, the issue of endogenous price regressors does not arise as prices are modeled as the outcome variable in a price equation rather than as an explanatory variable in product choice. Second, because the price equation requires utility to be denominated in money units we cannot re-scale utility to normalize the scaling parameter σ_ε. Third, the model has bargaining parameters.

Since we have data on transport costs we estimate transport cost parameters α directly in a first step using the regression model $T_{ij} = \alpha_0 + \alpha' z_{ij}^{(2)} + \zeta_{ij}$ where T_{ij} denotes observed transport costs (in monetary units) in project i per unit of volume. We assume that ζ_{ij} is such that $E[\zeta_{ij} | 1, z_{ij}^{(2)}] = 0$. The estimated values of parameters α—and therefore the transport costs $[\alpha' z_{ij}^{(2)}]$ for each i and j—are then treated as known when maximizing the likelihood with respect to remaining parameters and play a role similar to a consumer-varying price variable in identification (as discussed in the next paragraph). α_0 is absorbed into mean utility δ_j (see equation (13)).[34]

Remaining utility parameters are identified using standard discrete-choice arguments. The covariance between project-product interaction variables $[z_{ij}^{(1)}]_{j \in \mathcal{J}}$ and product choice is informative about the taste parameters β. The mean utility effects δ are obtained, given any θ, by matching predicted and observed product market shares (since the model satisfies the conditions in Berry et al. (2013)). The covariance between product choices and fitted transport costs $[\alpha' z_{ij}^{(2)}]$ is informative about σ_ε. The covariance (across region-years m) between observed surplus-shifters for inside goods and outside good market shares s_{m0} is informative about σ_J.

Turning to the cost parameters we leverage the transaction-level information in the price. The covariance between price and cost-shifters w_{ij}^c is informative about marginal cost parameters γ. The relationship between price and quantity q_i is informative about the transaction-specific fixed cost γ_0. The variance of prices, holding fixed the GEV parameters, is informative about the parameter σ_ν on the transaction-specific cost shock.

The bargaining parameters impact on prices so we turn to the pricing equation to

product j for the 4-year period of the data, is given by $\Sigma_i d_{ij}/N$ where $N = |\mathcal{I}_J| + \sum_{m \in \mathcal{M}} N_{0m}$ is the total number of projects inducing those that use the outside good. We use a convergence criterion of $\left\| \delta^{\iota+1} - \delta^{\iota} \right\| < 1 \times 10^{-12}$.

[34] The transport cost parameters α can be identified without using observing transport costs, using the same information that is useful for identifying the β parameters, namely variation in choice sets and chosen products across projects. Note also that transport costs were not available from one of the four manufacturers; we assume these observations are missing at random.

discuss their identification. Let j and j' be the first-best and runner-up goods respectively, so that surplus advantage $\Delta w_i = w_{ij} - w_{ij'}$, and price $p_{ij} = c_{ij} + \min\ [b_{ij}(w_{ij} - w_{i0}), w_{ij} - w_{ij'}]$, where, by definition, $(w_{ij} - w_{i0}) \geq (w_{ij} - w_{ij'}) > 0$. Note that variation in $(w_{ij} - w_{ij'})$ across projects is fully passed through to price if $b_{ij} = 1$ and has no impact if $b_{ij} = 0$. Despite the runner-up j' being unobserved, the data are informative about $(w_{ij} - w_{ij'})$. This is because we observe (i) the distance between project i and the chosen product j and (ii) the distances between i and products in the set $\mathcal{J} \setminus \mathcal{J}_k$ of candidates for runner-up j'. Hence, other things equal, a project for which (i) is unusually low, or the minimum value of the distances in (ii) is unusually high, will have a relatively high value of $(w_{ij} - w_{ij'})$. Two bargaining parameters enter b_{ij}: η_1 determines the average level of b_{ij} and η_2 determines how it varies with buyer-manufacturer size difference. Thus, conditional on observing first-best product j, the observed covariance of price with observed shifters of $(w_{ij} - w_{ij'})$ is informative about η_1 and the observed covariance of price and buyer-manufacturer size difference y_{ij} is informative about η_2.

5 Estimates and model fit

Parameter Estimates The transport cost parameters α in Panel A of Table 4 are estimated in a first step by regression. The remaining parameters in Panels B-D are estimated by maximum likelihood; there is a separate set of likelihood estimates for the bargaining and the TIOLI specifications.[35] To help with interpretation note that the model is scaled in units of £100 per 1000 bricks.

The estimates for α imply an average transport cost (for $i \in \mathcal{I}_J$) of £23.74 per 1000 bricks, which is 13% of average unit prices (£182.26 per 1000) reported in Table 1. These costs vary across projects, depending on distance and annual fuel prices: the 1st and 99th percentiles (for $i \in \mathcal{I}_J$) are £9.30 and £50.11 per 1000 bricks respectively, consistent with executive testimony in CC (2007).[36] The negative coefficient on the square of distance is consistent with the choice model estimates in Section 2.

Turning to utility parameters β in Panel B, there is a positive home-region taste effect for each of the two home-region variables used, and projects in the north have positive effects for red bricks and wire-cut bricks. Rainfall has a negative synergy with brick absorption and frost has a positive synergy with brick strength. All these signs are as expected. The GEV parameters σ imply that the εs for inside goods are positively

[35] We adjust standard errors as in Murphy and Topel (1985) to account for two-step estimation.

[36] Paragraph 4.60 of CC (2007) states that companies told the CC that "transport costs could be up to nearly one-quarter of the cost of delivered bricks". The mean production cost reported later in this section (Panel D, Table 6) is about £167 for 1000 bricks. The 99th percentile transport cost, £50.11, is 23% of the cost of delivered bricks, £50.11 + £167.00 = £217.11.

A: *Transport cost parameters*					
DST_{ij}	α_1	(100km)		0.116	(0.004)
$DST_{ij} \times \mathrm{w}_i$	α_2	(100km × £/L)		0.048	(0.004)
DST_{ij}^2	α_3			-0.010	(0.001)
R^2				0.825	
B: *Parameters in valuation* v_{ij}		Bargaining		Price-taking	
Same-region-produced	β_1	0.023	(0.004)	0.015	(0.003)
Within-100km-produced	β_2	0.040	(0.004)	0.017	(0.003)
North × red	β_3	0.046	(0.006)	0.041	(0.005)
North × wirecut	β_4	0.127	(0.007)	0.114	(0.006)
Absorption × rainfall	β_5	-0.048	(0.045)	0.015	(0.039)
Strength × frost	β_6	0.267	(0.128)	0.103	(0.112)
GEV nesting	σ_J	0.615	(0.023)	0.769	(0.019)
GEV scaling	σ_ε	0.208	(0.008)	0.145	(0.003)
Product effect ($\bar{\delta}$ is mean δ_j)	$\bar{\delta}$	0.861	(0.015)	0.553	(0.014)
C: *Parameters in cost* c_{ij}					
Gas price index	γ_1	0.881	(0.030)	0.918	(0.023)
Wages (£10k/year)	γ_2	0.412	(0.048)	0.196	(0.035)
Low-quality product (1/0)‡	γ_3	-0.038	(0.007)	-0.038	(0.007)
Plant effect ($\bar{\gamma}$ is median)	$\bar{\gamma}$	0.792	(0.059)	1.079	(0.044)
Fixed per-transaction cost	γ_f	0.151	(0.029)	0.138	(0.029)
Scaling term for cost shock	σ_ν	0.071	(0.001)	0.069	(0.001)
D: *Bargaining parameters*					
Manufacturer dummy $1[l \in \mathcal{K}]$	η_1	1.145	(0.122)	-	-
Agent l size y_l	η_2	0.265	(0.046)	-	-
Log likelihood		-46299.014		-446476.686	
LR test statistic $\backsim \chi^2(2)$		355.345		–	

E: *Manufacturer relative bargaining skill* $b_{ik(j)} \in [0,1]$

	Bargaining	TIOLI
Mean	0.540	1
SD	0.061	0
Min	0.401	1
Max	0.702	1

Notes. Panel A: regression of transport costs; observations: 11,855. Panels B-D: estimates by maximum likelihood. Observations: $N = |\mathcal{I}_J| + \Sigma_m N_{0m} = 19,036$. Specifications include regional and buyer-manufacturer dummies in value and plant dummies in cost. $\bar{\delta}$'s standard error obtained by regressing $(\delta_j)_{j \in \mathcal{J}_J}$ on a constant. ‡Indicator for whether a brick has a below-median ratio of strength to water absorption. LR test statistic is for the restriction imposed by the TIOLI model. The 0.1% significance level for the χ^2 distribution with 2 d.f. is 13.82. Statistics in Panel E for $b_{ik(i,1)}$ are for $i \in \mathcal{I}_J$. Units for transport costs and surplus estimates is £100 per 1000 bricks. Standard errors in parentheses; those in panels C-D are adjusted to account for two-step estimation.

Table 4: Estimated parameters

	External (a)	External (b)	Predicted
Unit cost c in £/1000 bricks	167.75	170.00	167.89

Notes: The predicted unit cost is $\Sigma_{i\in\mathcal{I}_J} c_i / \Sigma_{i\in\mathcal{I}_J} q_i$ where costs c_i are simulated as in footnote 39. The external cost measures are averages of plant-month level unit costs. Measures (a) and (b) are for plants for which respectively 90% and 99% of volume is facing bricks.

Table 5: External validation: comparison with external cost data

correlated. There are three further groups of unreported utility parameters: product-specific effects δ_j, dummies that allow regional variation in tastes for inside goods, and effects that allow buyer-specific preferences over manufacturers.[37]

Cost estimates are in Panel C. As expected, gas prices and wages have a positive effect, and low-quality bricks have a negative effect. We estimate effects for each of the 36 plants which are not reported. The per-transaction fixed cost parameter γ_f is small, about £15 per transaction or 9% of the average unit cost of 1000 bricks, which has an insignificant effect on unit costs except in the smallest transactions. The spread parameter σ_ν on project-specific costs implies a standard deviation of about 4% of average unit costs.

The bargaining skill coefficients in Panel D comprise a manufacturer effect η_1 and an effect for agent size η_2. Panel E reports the implications of these effects for the bargaining parameter $b_{ij} = b_{k(i,1)}/(b_{k(i,1)} + b_{h(i)})$. The mean of $\{b_{ij}\}_{i\in\mathcal{I}_J}$ is 0.540 which indicates similar bargaining skill between manufacturers and sellers. The table shows the variation around this mean because of relative agent size.

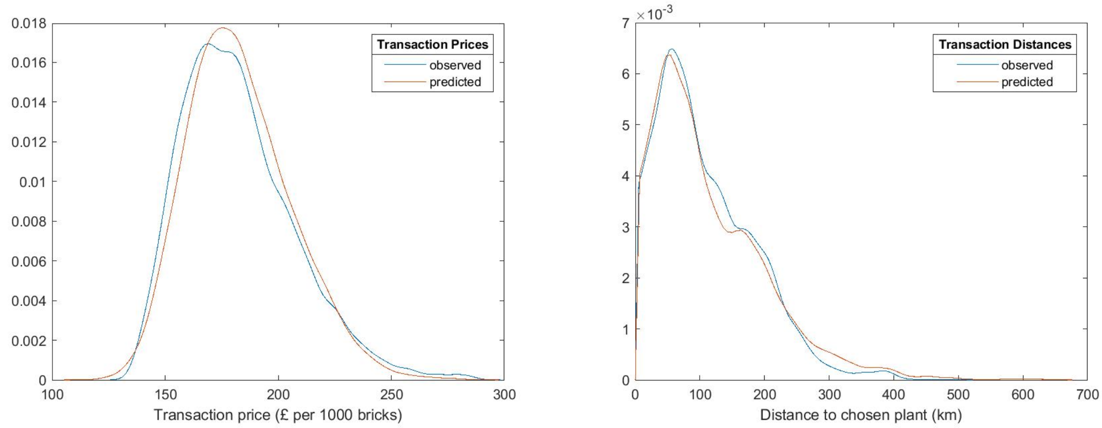
Likelihood ratio test of TIOLI pricing The TIOLI model is nested within the bargaining model and is obtained by imposing the constraint $b_{ij} = 1$. This eliminates the two bargaining parameters. Thus, we can test the hypothesis that $b_{ij} = 1$ using a likelihood ratio test. The test statistic in Table 4 exceeds the critical value 13.82 of the $\chi^2(2)$ distribution at a significance level of 0.1% so we reject the restriction.[38]

External cost validation To consider the fit of the bargaining model we simulate a price, cost, and product choice prediction for each $i \in \mathcal{I}_J$ conditioning on an inside good being chosen and on the project's observed characteristics.[39] In the case of cost

[37] If a buyer never trades with a manufacturer we drop it from the choice set; equivalent to setting its buyer-manufacturer effect to a large negative number. On average across in $i \in \mathcal{I}_J$ the buyer $h(i)$ trades with 3.6 of the 4 manufacturers in the 4-year period of the data.

[38] See the section 4.3 for a discussion of the identification of the bargaining parameter.

[39] For each i we draw a realization from $G_{\nu|J}(x_i)$, the distribution of ν_i conditional on choice of an inside good, a product $j \in \mathcal{J}_J$ using conditional choice probabilities $[s_{j|J}(x_i)]_{j\in\mathcal{J}_J}$ (from which ν_i cancels out), and a price from conditional density $f_j^*(p|x_i, y_{ij}, \nu_i)/s_j(x_i)$. The simulated j choice and



Notes: The observed data are per-unit prices and distances for $i \in \mathcal{I}_J$ in the full sample period. Predicted outcomes from the model are simulated for each project, conditional on choice of an inside good and observable type, as described in footnote 39.

Figure 2: Distance and price densities

predictions, Table 5 compares them with external cost data which was not used in estimation. These data, supplied by the manufacturers, consists of operating costs C_n for each plant-month n for the plant-months covered by the transactions data. We compute unit costs using $(1/|\mathcal{N}|) \times \Sigma_{n \in \mathcal{N}}(C_n/Q_n)$ where Q_n is the number of delivered bricks for n and $\mathcal{N}$ is the set of plant-months. Given that some plants produce a wider set of products than the type of brick we study (namely facing bricks), we limit $\mathcal{N}$ to plants that specialize in facing bricks. Definitions (a) and (b) use plants in which facing bricks are 90% and 99% of output respectively ($|\mathcal{N}|$ being 182 and 106). The model's unit cost prediction is calculated as $\Sigma_{i \in \mathcal{I}_J}(c_i q_i)/\Sigma_{i \in \mathcal{I}_J} q_i$, where c_i is simulated for transaction i. We do not expect a particularly close match with the cost data, as the predicted and observed concepts do not exactly correspond, mainly because of differences between accounting and economic cost concepts. Subject to this caveat, the match between the model's prediction and the external cost data provides a useful validation of the model.

Informal model fit As a further fit check we compare observed and simulated prices and distances (to product choices) in the densities in Figure 2 and Table 6. In Panels A-C of the table we consider price fit from a number of angles, including a measure of the within-product standard deviation, a decomposition by transaction size, and a decomposition by relative agent size. Panel D reports statistics on distances. We regard the overall fit of prices and distances as good.

cost shock ν_i imply a cost c_i which is used in the cost validation exercise.

	Observed	Predicted
A: Price (£/1000 bricks)		
Mean	182.26	182.99
Standard deviation	24.84	23.05
Pooled standard deviation (product groups)	14.74	14.63
B: Mean price, transaction quantity		
Smallest 25% (of transactions)	179.21	181.03
Largest 25%	186.48	184.93
C: Mean price, buyer/manufacturer size ratio		
Smallest 25% (of transactions)	190.64	191.48
Larges 25%	177.77	179.01
D: Distance (km) DST_{ij}		
Lower quartile	51.42	49.34
Median	91.62	91.22
Upper quartile	157.90	165.19

Notes: The simulated values are calculated as described in footnote 39. Statistics are for $i \in \mathcal{I}_J$ in the full sample period.

Table 6: Fit: prices and distances

6 Markups, pricing policy and concentration

In this section we analyze market power and mergers with individualized pricing. We calculate equilibrium markups under actual and counterfactual pricing policies and concentration levels. To avoid inter-year cost variation we consider a single year, 2005; in this section the results, and set notation $\mathcal{I}$ and $\mathcal{I}_J$, include only projects for 2005.

Elasticities, diversion ratios and surplus advantage The standard approach to assessing market power uses demand elasticities. In the model, however, negotiated prices vary across projects for the same product, and tend not to leave buyers marginal between first-best and runner-up products. Thus, we instead compute elasticities with respect to cost. To do this we change the component $c_j = \gamma \mathrm{w}_{ij}^c$ of unit cost, which, for any j, is common across i for a given year. The own-product cost elasticities in Panel A of Table 7 are on average -12.80. To show the impact of spatial differentiation, Panel A compares the cross-elasticities of product pairs with low and high inter-product distances; as expected, those pairs with low inter-product distance have higher cross-elasticities than those with high inter-product distance.

To measure the importance of multi-product ownership, we calculate the diversion ratio from product j (with respect to c_j) to other products of manufacturer $k(j)$. This diversion ratio is 0.42 on average across products. It varies quite substantially across

A: Elasticities and diversion ratios wrt cost of product $j \in \mathcal{J}_J$			
		Mean	SD
Own-elasticity		-12.80	1.37
Cross-product elasticity	10% of product pairs with lowest inter-product distance	0.29	-
	10% of product pairs with highest inter-product distance	0.07	-
Diversion ratio	to firm $k(j)$'s products	0.42	0.17
	to inside products	0.88	0.03
B: Surplus advantage of first-best Δw_i for $i \in \mathcal{I}_J$			
£/1000 bricks		Mean	SD
With portfolio effects	$\Delta w_i = w_{ij(i,1)} - w_{ij(i,2)}$	20.07	17.79
Without portfolio effects	$\Delta w_i = w_{ij(i,1)} - \max_{j \in \mathcal{J} \setminus j(i,1)} w_{ij}$	13.51	12.73

Notes In Panel A the unit of observation is the product ($j \in \mathcal{J}_J$). Elasticities are with respect to $c_j = \gamma \mathrm{w}^c_{ij}$. Cross elasticities are for top and bottom decile of product pairs by distance between products. The two diversion ratios are defined as follows, respectively: $1 - (\partial s_{k(j)}/\partial c_j)/(\partial s_j/\partial c_j)$ and $1 - (\partial s_J/\partial c_j)/(\partial s_j/\partial c_j)$ where $s_{k(j)}$ is the market share of manufacturer k and s_J is the market share of all inside goods. In Panel B the unit of observation the project ($i \in \mathcal{I}_J$).

Table 7: Demand elasticities, diversion ratios, and surplus advantage

products, mainly because manufacturers vary in portfolio size. The mean diversion ratio to inside products as a class, including those of manufacturer $k(j)$, is 0.88; this exceeds the joint market share of inside products (which is 0.728 on average across region-years, see Section 2), which indicates that inside goods tend to be closer substitutes for each other than for the outside good.

We now consider the model's implications for per-unit surplus advantages $\{\Delta w_i\}_{i \in \mathcal{I}_J}$. These are a key determinant of markups and for any transaction can be decomposed into a utility and a cost difference as follows

$$\Delta w_i \equiv w_{ij(i,1)} - w_{ij(i,2)} \;=\; [v_{ij(i,1)} - v_{ij(i,2)}] - [c_{ij(i,1)} - c_{ij(i,2)}]. \tag{29}$$

The utility difference includes the effects of both spatial and non-spatial differentiation.

An important factor that affects the utility and the cost differences is the first-best manufacturer's product portfolio $\mathcal{J}_{k(i,1)}$, which determines the residual set $\mathcal{J} \setminus \mathcal{J}_{k(i,1)}$ that are candidates to be the runner-up. With individually-negotiated prices, a portfolio effect on price arises if the first-best manufacturer owns the "second best" product, or "second and third best" etc., increasing the surplus difference with the runner-up above the level that would be obtained with single-product manufacturers.

Panel B presents statistics for the simulated sample $\{\Delta w_i\}_{i \in \mathcal{I}_J}$.[40] The table shows substantial cross-project variation. To evaluate the importance of portfolio effects in the

[40]For each i we calculate Δw_i by simulating price, cost, and $j(i,1)$ as in footnote 39 setting $b_{ij} = 1$ (as in TIOLI) and using the TIOLI result that $p_{ij(i,1)} - c_{ij(i,1)} = \Delta w_i$.

	Simulated PCMs $\{M_i\}_{i \in \mathcal{I}_J}$	Expected PCMs given locations $\{E[M \vert l_i]\}_{i \in \mathcal{I}_J}$	Expected distance minus mean distance $\{E[DST_{ij(i,1)} \vert l_i] - \widehat{DST}_i\}_{i \in \mathcal{I}_J}$
	(1)	(2)	(3)
Mean, $i \in \mathcal{I}_J$	0.080	0.082	-80.245
CV, $i \in \mathcal{I}_J$	0.738	0.159	–
Mean, bottom 10%	0.009	0.060	-69.958
Mean, top 10%	0.205	0.106	-153.587

Notes: Expectation operator E is with respect to observed and unobserved project type (see footnote 42). Top and bottom deciles refer to the top and bottom 10% of projects: in column (3) projects are sorted by the margin measure in column (2) and in the other columns by the margin measure in the same column. $\widehat{DST}_i = (1/|\mathcal{J}_J|) \times \Sigma_{j \in \mathcal{J}_J} DST_{ij}$ is mean distance from i to inside products.

Table 8: Market power: PCMs M_i.

mean and variation of the surplus advantage, we report a measure of Δw_i that subtracts portfolio effects, so that the runner-up is the "second-best" product after $j(i,1)$, i.e. it is selected from $\mathcal{J} \setminus j(i,1)$ rather than $\mathcal{J} \setminus \mathcal{J}_{k(i,1)}$. The table shows that portfolio effects substantially increase the mean of Δw_i. They also increase the variance, indicating that their relevance varies across transactions.

Market power To measure market power we simulate a PCM, denoted M_i, for each $i \in \mathcal{I}_J$, conditioning on observed characteristics (x_i, y_i).[41] The resulting sample $\{M_i\}_{i \in \mathcal{I}_J}$ is described in column (1) of Table 8. PCMs have a mean of 8.0%. This is consistent with CC (2007)'s assessment that, despite its high concentration, the industry is characterized by average or below-average profit levels. PCMs do however vary a lot across projects, with a coefficient of variation 0.738. Project location is one of a number of factors driving this variation. To isolate its role we obtain the expected markup conditional on location $E(M|l_i)$ for each $i \in \mathcal{I}_J$.[42] The results in column (2) show that about a fifth of the standard deviation of PCMs can be attributed to observed location.[43] To characterize locations of high- and low-PCM transactions we sort projects by $E(M|l_i)$. We find in column (3) that projects that have the greatest markups tend to have a relatively low distance to the first-best manufacturer, consistent with the manufacturer leveraging its transport cost advantage, and *vice versa*, a pattern known as "freight absorption" in the spatial pricing literature.

[41] We use the set of simulated prices and costs as simulated using the method in footnote 39.

[42] To do this, we integrate out, for each $i \in \mathcal{I}_J$, variables affecting markups other than observed location l_i. We follow the steps in footnote 39 repeatedly for each project i, where, in each repetition, we draw a value of x from g_x holding one component of x, namely l_i, at its observed level.

[43] This is a conservative estimate of the effect of location, since it does not account for the part of transport cost that is unobserved and included in ε (as discussed in Section 3.3).

Counterfactual pricing policies We now study the impact of individualized pricing on market power by comparing it with a counterfactual policy of uniform pricing. Since uniform prices do not necessarily induce the first-best choice, we write the choice indicator for product j in project i in a more general form. Let $\tau_i = (x_i, y_i, \nu_i, \varepsilon_i)$ denote the type of project i and let G_τ denote its distribution in the population. We write markups in the general form $\rho_\tau = (p_{\tau j} - c_{\tau j})_{j \in \mathcal{J}_J}$, where $p_{\tau j} = p_j(\tau)$ if individualized and $p_{\tau j} = p_j$ if uniform. Then the choice indicator can be written

$$d_{\tau j}(\rho_\tau) = 1\{w_{\tau j} - \rho_{\tau j} \geq \max[(w_{\tau j'} - \rho_{\tau j'})_{j' \in \mathcal{J}_J}, w_{\tau 0}]\}$$

and aggregate market share s_j, profit Π, and buyer surplus U, are given by[44]

$$\begin{aligned} s_j &= \mathbb{E}_\tau[d_{\tau j}(\rho_\tau)] \\ \Pi &= N \Sigma_{j \in \mathcal{J}_J} \mathbb{E}_\tau[q_\tau \rho_{\tau j} d_{\tau j}(\rho_\tau)] \\ U &= N \mathbb{E}_\tau[q_\tau \max((\omega_{\tau j} - \rho_{\tau j})_{j \in \mathcal{J}_J}, w_{\tau 0})]. \end{aligned}$$

In the uniform-pricing case, let prices $p = (p_k, p_{-k})$ where p_k is the vector for manufacturer k and p_{-k} is the vector for the other manufacturers. We assume multi-product Nash equilibrium so that markups are given by $\rho_i = (p_j - c_{ij})_{j \in \mathcal{J}_J}$ where prices solve

$$p_k(p_{-k}) = \arg\max_{p_k} \mathit{\Pi}_k(p_k, p_{-k}) \quad \forall k \in \mathcal{K}$$

and $\mathit{\Pi}_k(p_k, p_{-k})$ is the function that gives firm k's profits when prices are uniform.

In Table 9 we find that uniform pricing results in an increase in markups on average. Markups increase by 34% overall relative to baseline markups. The table decomposes this change into 25% from the change to TIOLI pricing and 9% from the change from TIOLI to uniform pricing.

Although uniform pricing increases markups on average it also reduces the variation of markups across projects. As a consequence a large minority of projects (31%) benefit. Panel B presents information on the distribution of percentage price changes across

[44] We do not condition on choice of an inside good here, since a change to uniform pricing can change whether a project chooses an inside good; to simulate demand and prices, we now follow the steps in footnote 39 except that instead of using $i \in \mathcal{I}_J$ (and their observable types x_i), we draw project characteristics from the density g_x. Using the GEV distribution for ε_i, we compute U as follows

$$U = \mathbb{E}_{\tilde{\tau}}[q_{\tilde{\tau}} \sigma_\varepsilon \ln\{1 + [\Sigma_{j' \in \mathcal{J}_J} \exp(\omega_{\tilde{\tau} j'} - (1 - I)\rho_{ij'})/\sigma_\varepsilon)]^{\sigma_J}\}] + I\Pi \tag{30}$$

where $\tilde{\tau}$ is project type up to ε and where I is an indicator for individualized pricing. When $I = 0$ (30) is the standard expression for buyer surplus. When $I = 1$ on the other hand socially efficient choices are always induced and the first term in (30) is total welfare and the second term Π is the part of total welfare that goes to the manufacturers.

A: Alternative pricing policies	Mean markups ($\bar{\rho}$) in £/1000			Mean	Market-level outcomes		
	All	Min 10%	Max 10%	$1_{[p<p_b]}$	s_J	U/U_b	Π/Π_b
[Mean p_b = £187.45]	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Individualized (bargaining, b)	15.22	1.07	43.46	0.00	0.75	1.00	1.00
Individualized (TIOLI)	19.01	1.30	55.53	0.00	0.75	0.87	1.25
Uniform pricing	20.40	15.60	24.91	0.31	0.56	0.89	0.97
B: Percentiles of distribution of % price changes for $i \in \mathcal{I}_J$.							
	P_1	P_{10}	P_{25}	P_{50}	P_{75}	P_{90}	P_{99}
Bargaining to uniform pricing	-16.94	-6.57	-1.08	4.35	9.65	14.32	21.68

Notes In Panel A, b denotes outcomes (prices p_b, buyer utility U_b and manufacturer profit Π_b) using the bargaining model. Statistics in columns 1-4 are based on all projects where an inside good is bought. Column 4 is the proportion of projects $i \in \mathcal{I}_J$ enjoying a lower price for the first-best good than the bargaining price. Column 5 is the market share of inside goods (s_J). Columns 6 and 7 report ratios of buyer and manufacturer surplus to the bargaining case. Panel B gives the percentiles for projects $i \in \mathcal{I}_J$.

Table 9: Counterfactual pricing policies

projects. The median price change is 4.35% but there is considerable variation around this: the bottom and top deciles of the price increase are -6.57% and 14.32% respectively. The market share for inside goods s_J falls because some efficient trades of inside goods do not take place with uniform pricing. Aggregate buyer welfare U falls by 11% and manufacturer surplus Π falls slightly.

Counterfactual ownership concentration: merger and demerger We now analyze counterfactual mergers and demergers that reallocate product ownership. We hold fixed the overall set of inside products $\mathcal{J}_J$, their production costs, and the set of bargaining parameters b_{ij} for each (i, j) pair. As well as merger simulations under the (factual) policy of individualized pricing, we also run them for the (counterfactual) policy of uniform pricing, to study the impact of pricing policy on merger effects.

When prices are individualized, a change in product ownership has an effect on the markup for project i only if it changes i's runner-up product. This is a different mechanism from the uniform pricing case. The effect of a merger is therefore limited to those projects whose first-best *and* (pre-merger) runner-up products are insiders to the merger (i.e. a subset of the projects buying from insiders to the merger). In contrast, with uniform pricing, outsider firms respond by raising prices—assuming that prices are strategic complements—and a merger affects all projects $i \in \mathcal{I}_J$.

First, we demerge to single-product firms. This counterfactual measures the market power that derives from multi-product ownership (i.e. portfolio effects). Comparing this market structure with the baseline, we see in Panel A of Table 10 that mean

A: Alternative market structures	Mean markups ($\bar{\rho}$) in £/1000 bricks						Market-level outcomes		
	mean	$\bar{\rho}-\bar{\rho}_a$	$k=1$	$k=2$	$k=3$	$k=4$	p_j	s_J	Π/Π_a
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Individualized pricing									
Baseline structure (a)	15.22	–	12.94	12.05	13.38	16.65	187.09	0.75	1.00
Single-product	11.55	-3.66	11.90	11.24	11.04	11.72	183.43	0.75	0.76
Merger1 $k \in \{1,2\}$	15.25	0.02	13.10	12.34	13.38	16.65	187.12	0.75	1.00
Merger2 $k \in \{3,4\}$	18.25	3.03	12.94	12.05	19.03	19.47	190.12	0.75	1.19
Uniform pricing									
Baseline structure (a)	20.40	–	17.06	15.46	18.85	23.12	193.96	0.56	1.00
Single-product	13.46	-6.94	13.50	13.15	13.39	13.51	186.82	0.64	0.75
Merger1 $k \in \{1,2\}$	20.69	0.29	17.62	16.49	18.91	23.25	194.26	0.56	1.01
Merger2 $k \in \{3,4\}$	24.68	4.28	18.30	16.24	27.84	27.79	197.45	0.52	1.09

B: Percentiles of the distribution of transaction-specific markup changes $\bar{\rho}-\bar{\rho}_a$							
Individualized pricing	P_1	P_{10}	P_{25}	P_{50}	P_{75}	P_{90}	P_{99}
Single-product	-0.03	-0.27	-0.89	-2.40	-5.28	-8.42	-18.03
Merger1 $k \in \{1,2\}$	0	0	0	0	0	0.01	0.77
Merger2 $k \in \{3,4\}$	0	0	0	1.81	4.26	7.88	18.31

Notes: Mean individualized (bargained) price in the actual structure is £187.45 (per 1000 bricks). Cost and markup units in £/1000 bricks. $\bar{\rho}_a$ denotes unit markup in the actual market structure. In Panel A, column (2) indicates the change in markup relative to the actual structure. Columns (3-8) show average markups by manufacturer. Column (7) is the average price across projects in £/1000 bricks. Panel B gives the percentile markup changes for projects $i \in \mathcal{I}_J$.

Table 10: Counterfactual market structure

markups (in £/1000) fall by 3.66. This is a drop of about 25%. Panel B shows that the drop (in £/1000) varies across projects: the bottom decile has a minor fall of 0.27 while the top decile has a fall of 8.42, which is about 30 times greater. This highlights that, with individualized pricing, the relevance of portfolio effects varies substantially across projects, so that the harm from the high level of ownership concentration that characterizes the industry is unequally distributed.

Second, we consider two counterfactual mergers: a merger of the two smallest $k \in \{1,2\}$ and the two largest manufacturers $k \in \{3,4\}$ respectively. The former, considered (and approved) in CC (2007), has a very small average effect on markups.[45] The latter, has, unsurprisingly, a much larger average effect. Under individualized pricing, it is relevant to analyze not just the mean but also the distribution of markup changes across projects in $\mathcal{I}_J$. In Panel B we see that the markup effects of the second merger

[45] Note the following caveats: (i) larger price increases would result if we allowed products for the merged entity to inherit the bargaining skill associated with the more skilled of the insiders to the merger, (ii) lower price increases would result if we allowed cost efficiencies, and (iii) as discussed in Section 2 the analysis is for national house-builders, which are a subset of the manufacturer's customers.

Buyer's disagreement point			Counterfactual pricing policy/market structure					
			Uniform pricing		Demerger, $\Delta\bar{\rho}$		Merger 2, $\Delta\bar{\rho}$	
	c	ρ	$\rho_u - \rho$	$1_{[\rho_u<\rho]}$	P_{50}	P_{90}	P_{50}	P_{90}
Baseline (w_{i0})	167.89	15.22	5.18	0.31	-2.40	-8.42	1.81	7.88
Alternative ($w_{ij(i,2)}$)	167.39	14.81	4.18	0.22	-2.63	-9.34	2.30	9.97

Notes: Cost and markup units in £/1000 bricks. The first four columns are averages of $i \in \mathcal{I}_J$ and the last four are percentiles of $i \in \mathcal{I}_J$. ρ_u denotes markup in a uniform pricing policy. P_n denotes the nth percentile of change in markup $\Delta\bar{\rho}_i$ from counterfactual product ownership.

Table 11: Robustness to alternative disagreement point in bargaining model

are unequally distributed, and are highly concentrated on the worst-affected decile.

To compare the effects of the same changes to ownership concentration under different pricing policies, we present merger and demerger results for uniform pricing in Panel A. The comparison can be summarized in four points. First, for any given market structure, average markups are always higher under uniform pricing (and not just at the observed market structure as we saw in Table 9). In other words, the relationship between average markups and concentration is shifted in a more competitive direction by individualized pricing. Second, markups increase only for (a subset of) transactions with insider firms under individualized pricing, but increase for *all* firms under uniform pricing; we see this from the reported firm-wise impacts in Panel A. Third, individualized pricing abates the average markup-increasing effects of a concentration-increasing merger—the average markup change in the table for any given concentration increase is always lower under individualized than uniform pricing—suggesting that the relationship between average markups and concentration is also flattened by individualized pricing. Fourth, despite the lower average effects, under individualized pricing, the distribution of effects from merger is much more unequal across transactions, such that large adverse competitive effects can arise for targeted transactions, and for some of these the harm can be greater than under uniform pricing.

Robustness As a robustness check, we also estimate the alternative bargaining model (see Section 3). Estimated parameters are reported in Appendix B. Table 11 shows that equilibrium outcomes are similar to baseline model. Columns 1 and 2 give costs and markups at the observed market structure. Columns 3 and 4 give the mean change in markups, and the proportion of transactions in which prices fall, under the uniform-pricing counterfactual. The last four columns give percentiles of changes to markups in the demerger counterfactual and the second merger counterfactual.

7 Conclusions

In many markets buyers make a choice of product, and negotiate an individualized price. This is particularly common in decentralized markets for intermediate goods with a small number of agents on each side of the market. Theoretically, relative to uniform pricing, this can have a major impact on market power and the effects of mergers. We develop a model of competition in such a setting, in which the runner-up good plays a key role. The model is founded in non-cooperative models of multi-seller bargaining, where the buyer makes a discrete choice between alternative options, but has not previously been applied empirically in the discrete choice demand literature. We derive a joint likelihood for the buyer's choice and price, which gives a convenient form for use with transactions data giving information on the chosen product and negotiated price in each transaction, and accounts for the unobservability of the runner up good and its negotiated price.

We estimate the model for the brick industry in Great Britain. Despite its high ownership concentration, we find that market power is low on average, consistent with CC (2007), but varies across transactions depending on buyer location and whether the manufacturer enjoys multi-product effects for that transaction. A uniform-pricing counterfactual increases markups on average but not for all transactions. Pricing policy has a major impact on merger effects, consistent with Cooper et al. (2005): comparing the same merger under the two pricing policies, individualized pricing reduces the mean price effect, but increases the effect in a small number of transactions.

The results have implications in at least two public policy areas. First, in the debate over price discrimination—e.g. surrounding enforcement of the Robinson-Patman Act in the US, and in the comparison of alternative pricing policies for delivered materials—they provide empirical support for the view that a switch from uniform to individualized pricing brings lower markups for most if not all buyers. Second, the results provide empirical support for the view that individualized pricing should be accounted for in merger policy: it can shift the relationship between market power and concentration in a more competitive direction, and can abate the average markup-increasing effect of mergers, although it can have adverse impacts for some buyers.

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A Derivation of Results in Sections 3 and 4

Section 3

TIOLI equilibrium The two best reply functions are

$$\rho^N_{j(n)}(\rho_{j(n')}) = \max[0, \rho_{j(n')} + w_{j(n)} - w_{j(n')} - \iota_n], \text{ for } n \in \{1,2\} \text{ and } n' = \{1,2\} \setminus \{n\}.$$

We assume $w_{j(1)} - w_{j(2)} > 0$, $\iota_2 > 0$ (where ι_2 is small), and $\iota_1 = 0$. Since $\rho^N_{j(1)}(0) = w_{j(1)} - w_{j(2)}$ and $\rho^N_{j(2)}(w_{j(1)} - w_{j(2)}) = 0$, markups $\rho_{j(1)} = w_{j(1)} - w_{j(2)}$ and $\rho_{j(2)} = 0$ are a Nash equilibrium. To check it is unique we determine if the two best-reply functions intersect at a positive runner-up margin. For any $\rho_{j(2)} > 0$, the first-best's best-reply function is $\rho^N_{j(1)}(\rho_{j(2)}) = w_{j(1)} - w_{j(2)} + \rho_{j(2)}$. Plugging this into the runner-up's best-reply function gives $\rho^N_{j(2)}(w_{j(1)} - w_{j(2)} + \rho_{j(1)}) = \rho_{j(2)} - \iota_2$ which is less than $\rho_{j(2)}$, so the two functions do not intersect.

Bargaining equilibrium The two bargaining functions are

$$\rho^B_{j(n)}(\rho_{j(n')}) = \min\left[b_{ik(n)}(w_{j(n)} - w_0), \rho^N_{j(n)}(\rho_{j(n')})\right] \tag{31}$$

$$= \min\left[b_{ik(n)}(w_{j(n)} - w_0), \max[0, \rho_{j(n')} + (w_{j(n)} - w_{j(n')}) - \iota_n]\right] \tag{32}$$

for $n \in \{1,2\}$, $n' = \{1,2\} \setminus \{n\}$. We assume $(w_{j(1)} - w_0) > (w_{j(1)} - w_{j(2)}) > 0$, $(w_{j(1)} - w_0) > (w_{j(2)} - w_0) > 0$, $\iota_2 > 0$ (where ι_2 is small), and $\iota_1 = 0$. Since $\rho^B_{j(1)}(0) = \min[b_{ik(1)}(w_{j(1)} - w_0), (w_{j(1)} - w_{j(2)})]$ it follows that $\rho^B_{j(1)}(0) \leq (w_{j(1)} - w_{j(2)})$ and by (32) that $\rho^N_{j(2)}(\rho_{j(1)}) = 0$ for all $\rho_{j(1)} \leq (w_{j(1)} - w_{j(2)})$. Hence markups $\rho_{j(1)} = \min[b_{ik(1)}(w_{j(1)} - w_0), (w_{j(1)} - w_{j(2)})]$ and $\rho_{j(2)} = 0$ solve the system in (31). To show this is unique we check the bargaining functions do not intersect for markups $\rho_{j(2)} > 0$. We do this for two cases. First, consider the case $b_{ij(1)}(w_{j(1)} - w_0) \geq \rho_{j(2)} + (w_{j(1)} - w_{j(2)})$. At markups $\rho_{j(2)} > 0$ satisfying this inequality, the first-best bargaining problem is constrained by the outside option. Hence the bargaining function $\rho^B_{j(1)}(.)$ is identical to the best reply function $\rho^N_{j(1)}(\rho_{j(2)}) = w_{j(1)} - w_{j(2)} + \rho_{j(2)}$. Plugging this into the runner-up's bargaining function (31) we get *at most* $\rho^N_{j(2)}(w_{j(1)} - w_{j(2)} + \rho_{j(2)}) = \rho_{j(2)} - \iota_2$ which is less than $\rho_{j(2)}$. Second, consider the case $b_{ij(1)}(w_{j(1)} - w_0) < \rho_{j(2)} + (w_{j(1)} - w_{j(2)})$. The first-best's bargaining problem is unconstrained by the outside good so the bargaining function is $\rho^B_{j(1)}(\rho_{j(2)}) = b_{ij(1)}(w_{j(1)} - w_0)$. Substituting $b_{ij(1)}(w_{j(1)} - w_0)$ for $\rho_{j(1)}$ in the runner-up's bargaining function (31) we get *at most* $\rho^N_{j(2)}(b_{ij(1)}(w_{j(1)} - w_0)) = b_{ij(1)}(w_{j(1)} - w_0) + (w_{j(2)} - w_{j(1)}) - \iota_2 < \rho_{j(2)}$ (where the last inequality is implied by $b_{ij(1)}(w_{j(1)} - w_0) < \rho_{j(2)} + (w_{j(1)} - w_{j(2)})$). Thus in neither case do the bargaining functions intersect.

Contract equilibrium We show that the equilibrium markups for the TIOLI, (baseline) bargaining, and alternative bargaining models, (in 7, 11, and 12), are all contracts equilibria. In a contract equilibrium (Cremer and Riordan (1987)) the agents in each bilateral problem maximize their joint surplus given the markup agreed in the other problem, i.e. for each $n \in \{1,2\}$ markup $\rho_{j(n)}$ is in the set

$$\rho_{j(n)}(\rho_{j(n')}) \in \arg \max_{\rho^* \in [0, w_{j(n)}]} \left\{ d_{j(n)}(\rho^*, \rho_{j(n')}) \times w_{j(n)} + d_{j(n')}(\rho^*, \rho_{j(n')}) \times [w_{j(n')} - \rho_{j(n')}] \right\}$$

where $n' = \{1,2\} \setminus \{n\}$. To see that the maximand is the bilateral surplus of buyer-manufacturer pair $(i, k(n))$ note that when $d_{j(n)} = 1$ the maximand is joint surplus $w_{j(n)}$ but when $d_{j(n')} = 1$, because $k(n)$ makes no sales, it is limited to net utility $w_{j(n')} - \rho_{j(n')}$. Negotiation $n = 1$ is bilaterally efficient iff $d_{j(1)} = 1$. This follows because $w_{j(1)} \geq [w_{j(2)} - \rho_{j(2)}], \forall \rho_{j(2)} \in [0, w_{j(2)}]$. Therefore contracts equilibrium requires both $d_{j(1)} = 1$ and bilateral efficiency in negotiation $n = 2$ and the latter obtains iff $w_{j(2)} \leq [w_{j(1)} - \rho_{j(1)}]$ (i.e. $\rho_{j(1)} \leq [w_{j(1)} - w_{j(2)}]$). The equilibroum prices in the TIOLI, (baseline) bargaining, and alternative bargaining models satisfy both conditions.

Alternative bargaining model In the alternative bargaining model the negotiated first-best markup solves the Nash bargaining problem in which $(w_{j(2)} - \rho_{j(2)}, 0)$ are the disagreement payoffs, i.e. $\rho^B_{j(1)}(\rho_{j(2)}) = \arg\max_{\rho'}[(w_{j(1)} - \rho') - (w_{j(2)} - \rho_{j(2)})]^{b_i} \times [\rho']^{b_{j(1)}}$. Assuming $\rho_{j(2)} = 0$ the solution is $\rho_{j(1)} = b_{ij(1)}(w_{j(1)} - w_{j(2)})$.

Section 4

Likelihood for the alternative model In the alternative model the markup equation can be written $\rho_{ij} = \min\{[b_{ij}(w_{ij} - w_{ij'})]_{j'\in\mathcal{J}\backslash\mathcal{J}_{k(j)}.}\}$ so that for $\rho \geq 0$

$$\rho_{ij} \geq \rho \iff w_{ij} \geq w_{ij'} + \rho \times (b_{ij}^{-1} 1_{[j'>0]} + b_{ij}^{-1} 1_{[j'=0]}) \quad \forall j' \in \mathcal{J}\backslash\mathcal{J}_{k(j)}. \tag{33}$$

Pooling the conditions in (15) and (33), and redefining $\chi_{jj'} = 1_{[j'\in\mathcal{J}\backslash\mathcal{J}_{k(j)}]} b_{ij}^{-1}$,

$$(j = j(i,1) \text{ and } \rho_{ij} \geq \rho) \iff w_{ij} \geq w_{ij'} + \rho(\chi_{jj'} 1_{[j'>0]} + b_{ij}^{-1} 1_{[j'=0]}) \quad j' \in \mathcal{J}. \tag{34}$$

Using the new definition of $\chi_{jj'}$ the expressions (24) and (25) follow, which in turn give the corresponding likelihood using Proposition 1.

Proposition 1 Let $S = 0$ and $S = 1$ for the baseline and alternative specifications. Suppress i subscripts. Let $\omega_j = \omega(x_j, \nu)$ and let $r_{-k|J} = \Sigma_{j'\in\mathcal{J}_J\backslash\mathcal{J}_k} r_{j'|J}$. Then, since $\partial(\omega_{j'} + \rho\chi_{jj'})/\partial\rho = 1_{[j'\in\mathcal{J}\backslash\mathcal{J}_{k(j)}]} \times b_j^{-S}$ when j' is an inside product, definitions in (25), and standard results of differentiation for nested logit functional forms, imply

$$\begin{aligned}
\frac{\partial r_{j|J}}{\partial\rho} &= -\frac{\sigma_\varepsilon}{\sigma_J} b_j^{-S} r_{j|J} r_{-k|J}, \\
\frac{\partial R}{\partial\rho} &= \frac{\sigma_\varepsilon}{\sigma_J b_j^S} \frac{\sum_{j'\in\mathcal{J}_J} \chi_{jj'} \exp\{\sigma_\varepsilon[\omega_{j'} + b_{ij}^{-S}\rho]/\sigma_J\}}{\sum_{j'\in\mathcal{J}_J} \exp\{\sigma_\varepsilon[\omega_{j'} + \chi_{jj'} b_{ij}^{-S}\rho]/\sigma_J\}} = \frac{\sigma_\varepsilon}{\sigma_J b_j^S} r_{-k|J}, \\
\frac{\partial r_J}{\partial\rho} &= \sigma_J r_J \frac{\partial R}{\partial\rho} - \exp\{\sigma_J R\} \frac{\partial}{\partial\rho} \frac{1}{\exp\{\sigma_\varepsilon\rho/b_j\} + \exp\{\sigma_J R\}} \\
&= \sigma_\varepsilon r_{-k|J} r_J b_j^{-S} - \sigma_\varepsilon r_J(1 - r_J) b_j^{-1} - \sigma_\varepsilon r_J^2 r_{-k|J} b_j^{-S} \\
&= -\sigma_\varepsilon r_J(1 - r_J)[b_j^{-1} - r_{-k|J} b_j^{-S}].
\end{aligned}$$

Since $r_j = r_{j|J} r_J$ it follows that

$$-\frac{\partial r_j}{\partial\rho} = -r_J \frac{\partial r_{j|J}}{\partial\rho} - \frac{\partial r_J}{\partial\rho} r_{j|J} = \sigma_\varepsilon r_j (r_{-k|J} b_j^{-S}/\sigma_J + (1 - r_J)[b_j^{-1} - r_{-k|J} b_j^{-S}])$$

so, using $r_{-k|J} r_J + r_k + r_0 = 1$ and $r_{-k|J} = 1 - r_{k|J}$, we have

$$-\frac{\partial r_j}{\partial\rho} = \begin{cases} \sigma_\varepsilon[r_j\{(1 - r_k) - (1 - \sigma_J^{-1})(1 - r_{k|J})\} - (1 - b_{ij}^{-1}) r_j r_0] & \text{if } S = 0 \\ \sigma_\varepsilon r_j[(1 - r_k) - (1 - \sigma_J^{-1})(1 - r_{k|J})] b_j^{-1} & \text{if } S = 1. \end{cases}$$

B For online publication: alternative model estimates

A: *Parameters in valuation* v_{ij}			
Same-region-produced	β_1	0.023	(0.004)
Within-100km-produced	β_2	0.043	(0.005)
North × red	β_3	0.048	(0.006)
North × wirecut	β_4	0.132	(0.007)
Absorption × rainfall	β_5	-0.038	(0.046)
Strength × frost	β_6	0.195	(0.129)
GEV nesting	σ_J	0.846	(0.023)
GEV scaling	σ_ε	0.167	(0.004)
Product effect ($\bar{\delta}$ is mean δ_j)	$\bar{\delta}$	0.525	(0.015)
B: *Parameters in cost* c_{ij}			
Gas price index	γ_1	0.919	(0.024)
Wages (£10k/year)	γ_2	0.230	(0.037)
Low-quality product (1/0)‡	γ_3	-0.036	(0.007)
Fixed per-transaction cost	γ_f	0.149	(0.029)
Scaling term for cost shock	σ_ν	0.073	(0.001)
Plant effect ($\bar{\gamma}$ is median)	$\bar{\gamma}$	1.037	(0.046)
C: *Bargaining parameters*			
Manufacturer dummy $1[l \in \mathcal{K}]$	η_1	-0.120	(0.081)
Agent l size y_l	η_2	0.225	(0.026)
Log likelihood			-46429.863
LR test statistic $\backsim \chi^2(2)$			93.647
D: *Manufacturer relative bargaining skill* $b_{ij} \in [0,1]$			
Mean			0.810
SD			0.045
Min			0.693
Max			0.908

Notes. These estimates use the alternative bargaining specification detailed in Appendix A. See notes for Table 4

Table 12: Estimated parameters: alternative bargaining specification

The estimates in Table 12 use the alternative bargaining specification detailed in Appendix A. The LR test statistic rejects the hypothesis of price-taking buyers at standard significance levels (as with the baseline specification). The parameters are similar to those found for the baseline model except for η_1 which implies a higher mean value across $i \in \mathcal{I}_J$ for the manufacturer's bargaining power b_{ij} (0.810 compared to 0.540). The difference is a consequence of the different magnitudes of bargained-over surplus: in the baseline the bargained-over surplus is $w_{ij(i,1)} - w_{i0}$, and in the alternative model it is $w_{ij(i,1)} - w_{ij(i,2)}$ which by definition is smaller. Since the markup represents the manufacturer's share of bargained-over surplus, a given markup for the manufacturer corresponds to a smaller surplus share in the baseline than in the alternative model.

C For online publication: Data

C.1 Variables in the deliveries dataset

We use a data set provided to us by the four main manufacturers that records each delivery of a brick variety within Great Britain (GB) in the period 2003-2006 from these firms. The smallest two of these firms, Baggeridge Brick and Wienerberger, merged in 2007, following the investigation reported in CC (2007). The dataset used here was also used in this investigation. The following is a complete list of the variables. We give the exact name of the variable as it appears in the data in square brackets [], the exact wording of the description of the variable as it appears in the data is in round brackets (), and the unbracketed words at the end are our own description of the variable.

1. Manufacturer information: (a) [Manufacturer], (Brick manufacturer), Name of the brick manufacturer; (b) [Plant code cat], (Plant code), Name of plant where the bricks were manufactured and from which delivery was made.

2. Buyer information: (a) [Buyer_name], Name of buyer; (b) [Town], Town to which delivery is made; (c) [Original postcode], Delivery postcode.

3. Delivery information: (a) [Price], (Transaction price (GBP)), The total payment for the delivery; (b) [Volume], (Volume bricks), The number of bricks in the delivery; (c) [Date], (Transaction date), The date on which the delivery and transaction happened; (d) [Delivery], (Delivery arrangement), Whether the delivery was arranged by buyer or manufacturer; (e) [Haulage price], (Haulage price (GBP)). Transportation cost.

4. Characteristics of the delivered product variety: (a) [Description], (Description of individual brick variety), The name of the product variety; (b) [Use_cat], (End use classification), Indicator variable for whether the delivered product variety is a facing brick or some other use type; (c) [Manuf cat], (Manufacturing process category), Classifies bricks by the way the brick is made, e.g. wire-cut, molded.

C.2 Geocoding deliveries and classification of buyer type

To obtain a grid reference we use the postcode which takes the form of two groups of alphanumeric variables e.g. OX1 3UQ with increasing geographic precision moving from left to right. The Central Postcode Directory (CPD), available from the the UK Post Office, gives a grid reference for each postcode. The address of each plant is public information. The project's postcode is in the variable [Original postcode] in section C.1. In some cases the postcode was recorded with error (a common feature of address datasets). Where part of the postcode is reported (e.g. OX1) we take the average of the grid reference points consistent with what is reported. Where the postcode did not appear in the CPD we search for the nearest postcode consistent with the most important letters in the postcode, starting with alternatives to the final letter, followed by alternatives to the final two letters, and so on, until available postcodes are found; where this results in multiple postcodes we take the average grid reference. Where the postcode was missing but the town in the postal address was given (i.e. the variable [Town] in section C.1) we use the postcodes consistent with this and take an average of their grid references. Finally, for one of the manufacturers, the delivery postcode was not recorded for 11.4% of its deliveries to the top 16 buyers (whereas for the other three suppliers there were very few missing address observations—1.014%, 0.004% and 0.000% respectively). To avoid mis-representing transactions for one manufacturer we dropped delivery addresses at random from each of the other three firms so that the same proportion of delivery addresses are removed for all manufacturers. We classify buyers as either a builder or merchant using the name of the buyer (i.e. variable [Buyer_name] in section C.1) and the business website associated with that name. The name of the same buyer sometimes appears in different forms for different deliveries—e.g. (i) "Taywood Homes" and "Taylor Woodrow Developments" and (ii) "PERS01" and "Persimmon Homes". In the case of (i) the former is a fully owned subsidiary of the latter; in the case of (ii) the former is a code name used for the latter firm. We checked ownership of all firm names to determine those that were under the same ownership in which case they were treated as being the same firm. Finally, where code names were used, we identified the builder that had the most consecutive letters in common with the code; as a safeguard against errors we checked by online search that delivery locations for code names in the data matched known housing projects from the matched building firm.

C.3 Products and characteristics

The deliveries dataset includes a limited number of product characteristics for each variety. We supplement these using the manufacturers' catalogs.[46] Figure 3 shows a page from a manufacturer's brick catalog, giving a list of varieties and their characteristics

[46]We are grateful to a number of students at Oxford University who provided research assistance obtaining product characteristics.

	TYPE	LOCATION	SIZE TOLERANCE		DURABILITY	ACTIVE SOLUBLE SALTS	COMPRESSIVE STRENGTH (N/mm²)	WATER ABSORPTION (%)	PACK QUANTITY	TYPICAL PACK WEIGHT kg
			MEAN	RANGE	EN 771-1	EN 771-1	EN 771-1	EN 771-1		
Bamburgh Red Stock	S	Todhills	T1	R1	F2	S2	≥20	≤14	500	1113
Bisque Red Multi	W	Waresley	T2	R1	F1	S2	≥25	≤24	500	1113
Blended Red Multi Gilt Stock	S	Waresley	T2	R1	F2	S2	≥21	≤24	500	1166
Blue Velvet	S	Hull & Dartford	T2	R1	F2	S2	≥12	≤15	528	1308
Blueberry Multi	W	Ewhurst	T2	R1	F2	S2	≥60	≤10	400	923
Brampton Blend	W	Cheadle	T2	R1	F2	S2	≥40	≤20	400	882

S = Stock W = Wirecut

Notes: The page is from the section for red bricks of a manufacturer's brick catalog. It lists 6 brick varieties and shows pictures of three of them. In the first two columns the type, listing whether the brick is wirecut (W) or molded (S), and plant location, of the brick are given and in the seventh and eighth the strength and water absorption.

Figure 3: Typical page from a brick manufacturer catalog

(along with pictures of some of the varieties). We obtain the following five characteristics, two of which are from the deliveries dataset and three from the brick catalogs. We have discretized the last two brick characteristics. For each product characteristic we note the the data source, the units (if applicable), the number of discrete alternative values, and why it is important to a buyer.

1. *Color* (2 colors). [Source: brick catalogs]. Important for aesthetic reasons. The alternatives are: buff (yellow) and red. A small number of brick varieties are listed as orange and we class these as red since they are very close in appearance. Different types of clay and hence different plants (located at different clay deposits) are associated with different brick shades within any given color.

2. *Plant* (36 plants). [Source: deliveries data set]. Important primarily for spatial reasons. However plant location also affacts visual appearance of the product (as described under color). This is lower than the total number of brick plants because we count co-located plants of the same firm as a single plant, we drop plants that produce non-facing bricks or low market share bricks.

3. *Manufacturing type* (2 types: wire-cut and molded). [Source: deliveries data set].

	Color	Shaping	Strength	Absorption	Plant
			N/m^2 (100s)	percent (100s)	
Number of discrete values	2	2	13	5	36
Set of categorical values	{R,Y}	{W,M}	-	-	{D,E,...}
Discretization interval			0.05	0.05	
Products [example varieties]					
Product 1 [Cheshire Red Multi, Bowden Red]	R	W	0.40	0.15	D
Product 2 [Hadrian Buff, Hadrian Bronze]	Y	W	0.60	0.10	T
⋮					
Product 75 [Arden Red Multi, Dorset Red Stock]	R	M	0.20	0.20	E

Notes. Number of products: 75. Number of varieties 416. The variables *strength* and *absorb* are defined in the text and are discretized to the nearest 0.05 units. D, E and T denote the Desford, Ellistow and Throckley plants; R and Y denote the colors red and yellow; W and M denote wire-cut and molded bricks.

Table 13: Classification of varieties into products by observable characteristics

The manufacturing type—i.e. the variable [Manuf_cat] in section C.1, which we refer to in the paper as *the shaping* method—is the method of cutting the bricks from clay. The two main shaping method alternatives are wire-cut and molded. This is an aesthetic characteristic as it affects the appearance of the brick. We include handmade, clamp, and softmud bricks (categories in the variable [Manuf cat]) in molded as they use the same shaping method as molded bricks.

4. *Compression strength* (in N/mm^2). We round strength to the nearest $5N/mm^2$, giving 13 distinct levels $(10, 15, \ldots, 70, 75)$. The compression strength is the maximum load at which a brick is crushed measured in Newtons per square millimeter. This variable, also known as *durability*, improves the performance of the brick in areas with exposure to frost attack.

5. *Water absorption* (units: % of mass): this variable is defined as $(m_2 - m_1)/m_1$ where m_1 is the mass of the brick when dry and m_2 is its mass after 24 hours of complete immersion in water. We round this to the nearest 5 percent, giving 5 distinct levels $(5, 10, \ldots, 20, 25)$. A lower level is a higher quality: bricks with low water absorption should be used in areas of high rainfall where there is a risk that brickwork will be persistently wet (see C.6).

Other technical characteristics listed in the catalog do not vary across the bricks considered by house builders in our data so we do not include them.[47] There are 416 distinct

[47]For a discussion of brick characteristics see Section 6 of Brick Development Association (2011) *Design Note* at *http://www.brick.org.uk/admin/resources/g-brickwork-durability.pdf.*

varieties in the transaction dataset and we classify these into 75 groups, referred to as *products*, using these five characteristics. The product classification is illustrated in Table 13. The table gives three example products, lists some illustrative varieties in each product, and gives their observable characteristics.

C.4 Determination of transaction dataset

The transaction dataset is obtained from the deliveries dataset in appendix C.1 as follows. We include deliveries of facing bricks in the years 2003-2006 from GB plants to one of the top-16 builders by volume over 2003-2006; in this appendix we refer to these deliveries as *brick sales*. The top-16 builders account for 94.1% of direct deliveries by volume in the data. We exclude pressed bricks (known as flettons, as indicated by the [Manuf_cat] variable, 1.2% of brick sales volume) which are not used for new houses. (They are used in the repair, maintenance, and improvement of existing houses, see CC (2007) paragraphs 5.8-5.10.) We drop deliveries of less than 5,000 bricks (3.1% of brick sales volume) to remove a tail of small deliveries that are likely to correspond to idiosyncratic requests and top-ups and which have some extreme unit prices; as a reference point, note that the median individual delivery to builders is 10,000 which represents both (i) approximately the number needed for an individual detached house and (ii) the typical capacity of a brick truck. We drop deliveries of brick varieties that are not buff (i.e. yellow) or red (0.04% of brick sales volume). A *transaction* is defined to be a buyer-variety-location-year (where location refers to the location of use); a variety implies a unique production location (its plant) so a transaction is associated with a unique pair of (production and use) locations. To remove a tail of small products we drop products (defined in C.3) with less than 7.5 annual transactions on average (which in total are 4.2% of brick sales volume). Table 14 presents information on the aggregation of the deliveries dataset to the transactions dataset. Panel A shows the number of deliveries and the number of transactions. Panel B shows the extent to which transactions vary in terms of the number of deliveries (a consequence of scale differences across projects) and the dominance of a modal price for deliveries within a transaction (a consequence of the negotiation of project price at annual rather than delivery level).

C.5 Institutional details

The prices are either agreed in a collection of concurrently-negotiated price agreements (known as framework agreements) or isolated agreements at other times (known as ad hoc agreements). The agreements are about conditions of trade and do not commit

A: Counts of deliveries and transactions		
Number of deliveries		110,726
Number of buyer-variety-location-years (i.e. transactions)		13,788
B: Summary statistics for deliveries in a transaction	Mean	SD
Number of deliveries in a transaction	8.031	7.978
Proportion (by volume) of deliveries in a transaction		
(i) sold at modal price for transaction	0.860	0.201
(ii) sold within 1% of modal price for transaction	0.924	0.152

Notes. The table reports statistics from the deliveries dataset before and after aggregation to transaction level. See text for the definition of a transaction

Table 14: Aggregation: deliveries to transactions

the buyer to purchase (CC (2007) para 4.65, 4.66). Buyers prefer not to hold stocks of bricks at their project locations and thus take a number of deliveries, sometimes at short notice, over time as the project proceeds. To facilitate this manufacturers hold large stocks of inventory (see CC (2007) paragraphs 4.44). Negotiations result in prices which vary across varieties, annual volumes, and locations for a given buyer as described in Section 2 and which hold good for a year.

C.6 Weather data

We use data from the UK Meteorological Office's *UKCP09* data series. This data series gives weather for each 5×5 km grid cell in the UK. We take the average of the 5×5 km grid cell values that fall within each NUTS1 region where the cell values are themselves averages measured between 1981-2010. Rainfall is measured of daily mm per square meter and frost by the total number of days of air frost per month.

C.7 Outside good share

The share of the outside good in region-year m is given by $s_{0m} = (H_m - B_m)/H_m$where H_m is the number of standardized houses needing cladding and B_m is the number that use bricks. To calculate B_m we use $B_m = kQ_m$ where k is the number of houses per brick and Q_m is the number of bricks delivered to market m by the manufacturers. We obtain k using $s_0 = 1 - k\Sigma_m Q_m/(\Sigma_m H_m)$ where s_0 (0.238) is the national share of the outside good in the period of the data, given by $s_0 = 1 - s_K s_N$ where s_K (0.850) is the share of the manufacturers in our study (CC (2007), para 5.46) and s_N (0.897) is the national proportion of new houses using facing bricks in the period of study is given as in the *English Housing Survey* published by the Department for Communities and Local Government (2008).[48] To calculate H_m we use the number of house building completions, from the UK's Office for National Statistics *House Price Statistics for Small Areas* (HPSSA).[49] Given lumpiness in the data on completions relative values across regions are constant for the period of the study. The relative value for region κ is $\varrho_\kappa = \Sigma_t H^*_{\kappa t}/\Sigma_\kappa \Sigma_t H^*_{\kappa t}$ where $H^*_{\kappa t}$ is completions in market $m = (\kappa, t)$. Then $H_m = \varrho_\kappa H^*_t$ where H^*_t is the 3-year moving average of total housing completions in Great Britain. This method is used because the timing of completions does not coincide exactly with the stage in a construction project's life cycle when brick delivery is needed and the data are somewhat volatile given the large size of individual housing projects being recorded. Similarly, we assume relative demand across regions for inside goods is stable over time and for region κ is given by $\varrho^Q_\kappa = \Sigma_t Q^*_{\kappa t}/\Sigma_\kappa \Sigma_t Q^*_{\kappa t}$ where $Q^*_{\kappa t}$ is observed bricks delivered. Then $Q_m = \varrho^Q_\kappa Q^*_t$, where Q^*_t is $\Sigma_\kappa Q_{\kappa t}$. The approach adopted here is consistent with the spatial distribution of projects detailed in footnote 32.

[48] This survey includes 2708 dwellings that were built recently (between 1990 and 2008) where a physical inspection was carried out between April 2007 and March 2009. Table 1.3 of this publication reports that the percentage of these dwellings that used facing bricks (referred to as "masonry pointing") as their predominant type of wall finish is 0.897.

[49] These data are recorded by category: (i) detached houses (that require cladding on all four sides); (ii) semi-detached houses (requiring cladding on three sides); (iii) terraced houses (requiring cladding on two sides); and (iv) apartments. This breakdown is not available in Scotland, where we assume the average proportions for the rest of Great Britain apply there. To aggregate we give a detached house a weight of 1, a semi-detached house 0.75, a terraced house 0.5 and an apartment a weight of 0.40; the last of these is based on CC (2007), paragraph 4.30.