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When trade drives markup divergence: An application to auto markets

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Abstract
When firms sell in multiple markets, estimates of markups from the demand-side will generally diverge from estimates based on the supply-side (e.g. via production functions). The empirical examination of the importance of this fact has been hampered by the absence of market-specific cost data. To overcome this, we show production markups can be expressed as the revenue-weighted average of demand-based markups across markets (and products). This highlights that a divergence in demand-based and production-based markups is due to the revenue shares and markups across foreign and domestic markets, factors that can be assessed with readily available trade data. Using data from auto firms producing in the UK, we show production-based markups increased between 1998 and 2018 whereas demand-based markups decreased. These trends can be reconciled by an increase in the markup that UK-based producers gained on their exports, which we corroborate using administrative trade data. We find that increases in production-based markups have been driven by exports, particularly to China where foreign brands command high markups.

Data Disclaimer: parts of this work were produced using statistical data from the UK Office for National Statistics ("ONS"). The use of ONS data does not imply the endorsement of the ONS in relation to its interpretation or analysis. Analysis using ONS research datasets may not exactly reproduce ONS aggregates and was carried out in the Secure Research Service, part of the Office for National Statistics.

Keywords: markup divergence, auto markets, supply and demand

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1 Introduction

Product market power has long been of interest to economists and policy makers. The difference between a firm's price and its marginal cost, the markup, is an attractive summary measure of market power (Berry et al. 2019), but because data on marginal costs are typically unavailable, these markups cannot be directly observed. Consequently, several estimators have been proposed to measure markups leveraging the first-order conditions of profit maximization. These markup estimation techniques can broadly be categorised into two approaches. The first, which we label a "demand-side" approach uses data on prices, purchase decisions, and consumer attributes to estimate price elasticities of demand. These, coupled with assumptions on firms' pricing behaviour, identify marginal costs and hence markups (Berry et al. 1995, 2004; Grieco et al. 2023). The second "production-side" approach uses data to estimate production function parameters which identify markups from the first-order condition of a variable input choice (Hall 1988; De Loecker and Warzynski 2012). These approaches have distinct advantages and disadvantages that are well-discussed in the literature (see below), as they require distinct assumptions (and data).

In this paper, we emphasize that demand-based and production-based markup estimates can diverge when firms sell to multiple markets with heterogeneous preferences, *even if the assumptions underpinning both estimators hold.* The divergence is due to the differences in the data. While demand-based estimation typically uses data on purchases and prices consumed within a particular country, production-based markup estimation usually uses data relating to the output of establishments located in a single country (even if this output is exported to overseas markets). Given that firms, even within narrowly-defined industries, often sell multiple products into multiple national markets it is clear that markups estimated by either approach will not necessarily align.

To make this explicit, we show that producer-side markups - defined either as the price-to-marginal cost ratio or the Lerner Index - can be expressed as revenue-weighted averages across markets (and products). De Loecker and Warzynski (2012) show a similar aggregation. They express producer-side markups as a *cost share*-weighted average of market-specific markups in order to provide suggestive evidence that firms obtain heterogeneous markups when they sell in foreign rather than domestic markets. However, our alternative aggregation offers the practical advantage that, unlike cost-shares, market-specific revenue shares are often observed either in firms' financial reports or in trade data. This allows a decomposition of the total producer-side markup into a domestic and a foreign components.

To demonstrate the utility of our method, we use data from the UK car market to estimate markups using both demand-side and production-side approaches. This is an attractive application for several reasons. Cars are commonly the second most expensive purchase for consumers (after housing), and hence markups can have substantial impacts on consumer welfare. Second, many papers on demand-side estimation focus on the car market, providing a benchmark for our findings. Third, other work shows that UK car manufacturers exhibited relatively strong productivity growth over the last four decades, that translated into higher wages (Norris Keiller et al. 2024). The interpretation of this performance as a 'success story', however, would be tempered if it were due to increased markups rather than productivity.

We assemble data necessary to estimate demand-side and production-side markups between 1998 and 2018. We find that production-based markups increased over this period, whereas demand-side markups fell. We then show that these trends can be reconciled if the markup gained by UK-based car manufacturers on their exports increased. About 80% of cars produced in the UK were exported. British consumers benefited from lower markups over this twenty year period, but UK-based factories enjoyed overall higher markups because so many cars were exported to high-markup locations (e.g. Jaguar cars in China).

One concern with this conclusion is that there may be other causes for the divergence between production-based and demand-based markup estimates, such as violation of the market conduct assumptions in the demand-based approach (static Bertrand Nash). To corroborate our findings, we therefore use customs data to relate changes in producer-side markups to changes in export revenue shares. We show that increases in firm-level markups are positively related to the growth in the revenue shares of Chinese (and US) exports, which have expanded rapidly over our sample period. This is consistent with our argument that rises in markups obtained by UK-based car manufacturers have not come at the detriment of UK-based consumers. Instead, they are driven by expansion into foreign markets where demand for British produced demands (e.g. Land Rovers) appears more inelastic.

Related literature

We make methodological and empirical contributions. Methodologically, we relate producer-based markup estimates to demand-based markup estimates using a simple aggregation formula. This draws a link between the firm-side estimates developed by De Loecker and Warzynski (2012) as an extension of the industry-level approach of Hall (1988), and the demand-based estimates developed by Berry et al. (1995). While De Loecker and Warzynski (2012) show a similar aggregation, their exposition weighs market-specific markups using cost-shares, which precludes decomposition in many empirical settings. We alternatively show that production-based markups, defined as either the price-marginal cost ratio or the Lerner index, can be expressed as revenue-weighted averages across markets and products. Given the availability of firm-specific revenues by market, our alternative aggregation is attractive as it allows one to decompose a given firms' markup into market-specific demand-based components.

Empirically, we document trends in producer and demand markups in the UK car market between 1998 and 2018. Similar to the production-based analysis of De Loecker et al. (2020) and De Loecker et al. (2022) covering the whole economy, we find that production markups among UK car manufacturers increased between 1998 and 2018. However, we find that demand-based markups fell and this divergence is broadly similar to Grieco et al. (2023) who analyse the US car market. Grieco et al. (2023) conclude that this reflects methodological problems with the production-based approach, we posit an alternative explanation, which is the importance of export markets for a smaller, more open economy like the UK.[1]

While the aforementioned literature examines markups using either the production or demand approach in isolation, our work is also closely related to De Loecker and Scott (2022). They contrast markups obtained from both approaches using data from the US brewing industry. Rather than trade, which is the focus of our paper, they highlight how the vertical structure of the industry may cause producer- and demand-based markup estimates to diverge if retailers exhibit a different competition structure to producers. Unlike our findings, they show markups have increased under both estimation methods which they conclude as evidence in support of perfect competition among retailers. Our work suggests that, even if retailers are perfectly competitive, production-based and demand-based markup estimates may diverge because of trade and therefore the test of retailer competition structure suggested by De Loecker and Scott (2022) is only suited to industries where the majority of production is sold domestically.[2]

Our paper also contributes to the literature on pricing and product variety in the car industry across international markets, specifically within the context of market power (such as Goldberg 1995; Verboven 1996; Goldberg and Verboven 2001). Additionally, studies by Berry et al. (1999) and Lacetera and Sydnor (2015) focus on the role of production locations and trade in the car market.

The rest of the paper is structured as follows. Section 2 lays out an aggregation formula showing production-based markups can be expressed as a revenue-weighted average across markets and products and derives an implied dynamic decomposition that expresses changes in markups as the sum of 'within' and 'between' components. Section 3 discusses the details of our empirical application. We provide a historical overview of major trends in the UK car market, describe the data and methods we use to estimate production as well as demand markups, and explain how we use our aggregation formula to infer the markup obtained by UK car manufacturers on their exports. We present our main results on markups alongside supplementary analysis of trade data that corroborates the increase in the export markup implied by our aggregation formula. Section 4 concludes.

2 Reconciling demand and production markup estimates

Start from the commonly-used assumption that markets can be defined as a country-product combination. Following from this, the price sensitivity of consumers in any market in combination with assumptions on firms' price-setting behaviour can be used to identify demand markups. Production markup estimation, by contrast, relies on firm-level data and since firms often sell multiple products into multiple national markets, estimates obtained via the two approaches are likely to diverge. In this section, we

1. Several recent papers study trends in demand-side markups in other industries. These include cement (Miller et al. 2023) and consumer packaged goods (Atalay et al. 2023; Döpper et al. 2023).

2. Supply Use Tables suggest around 98% of US-produced beer is consumed domestically, making this a second-order consideration in the De Loecker and Scott (2022) context.

make this explicit by showing how firm-level (i.e. production) markups can be expressed as revenue-weighted averages of market-product specific demand markups. The exact expression of this aggregation depends on whether one defines markups using the Lerner Index (i.e. the difference between price and marginal cost divided by price), or the ratio of price to marginal cost (PMC). We focus on Lerner index markups in our main analysis, since the aggregation formula it is more straightforward, but show how to decompose PMC markups in Appendix A.

Suppose firm i serves J perfectly separable national markets, $j \in [1...J]$. For each product, $k \in [1...K]$, the Lerner-index markup obtained by i in market j is

$$\mu_{ijk}^{L} = \frac{p_{ijk} - c_{ijk}}{p_{ijk}}, \tag{1}$$

where c denotes marginal cost and p denotes price. Multiplying the RHS of (1) by $\frac{q_{ijk}}{q_{ijk}} = 1$ gives

$$\begin{aligned} \mu_{ijk}^{L} &= \left(\frac{p_{ijk} - c_{ijk}}{p_{ijk}}\right)\left(\frac{q_{ijk}}{q_{ijk}}\right) \\ &= \frac{R_{ijk} - C_{ijk}}{R_{ijk}}, \end{aligned} \tag{2}$$

where R denotes revenue and C denotes cost of goods sold.[3]

Define firm i's market-specific aggregate markup in market j as

$$\begin{aligned} \mu_{ij}^{L} = \frac{R_{ij} - C_{ij}}{R_{ij}} &= \sum_{k=1}^{K} \frac{R_{ijk} - C_{ijk}}{R_{ij}} = \sum_{k=1}^{K} \left(\frac{R_{ijk}}{R_{ij}}\right)\left(\frac{R_{ijk} - C_{ijk}}{R_{ijk}}\right) \\ &= \sum_{k=1}^{K} \left(\frac{R_{ijk}}{R_{ij}}\right) \mu_{ijk}^{L}. \end{aligned} \tag{3}$$

This shows the aggregate markup that firm i obtains from market j is the revenue-weighted average of product-specific markups. Using a similar logic, we can aggregate over markets to obtain firm i's overall aggregate markup as a revenue-weighted average of their market-specific aggregate markups

$$\begin{aligned} \mu_{i}^{L} = \frac{R_{i} - C_{i}}{R_{i}} &= \sum_{j=1}^{J} \frac{R_{ij} - C_{ij}}{R_{i}} = \sum_{j=1}^{J} \left(\frac{R_{ij}}{R_{i}}\right)\left(\frac{R_{ij} - C_{ij}}{R_{ij}}\right) \\ &= \sum_{j=1}^{J} \left(\frac{R_{ij}}{R_{i}}\right) \mu_{ij}^{L}. \end{aligned} \tag{4}$$

3. For simplicity, this derivation assumes constant marginal costs with respect to quantity ($MC(q) = c$). In appendix B, we show that a similar formula can be derived without making assumptions on the shape of the marginal cost curve.

This demonstrates the conceptual difference between demand and production markup estimates: the data deployed by the former in effect estimate a market-product-specific μ^L_{ijk}, whereas the latter seek to estimate the aggregate firm-specific μ^L_i.

As is the case with other aggregate concepts, one can attribute changes in firm-level aggregate markups to across-market changes (i.e. changes in market revenue shares) and within-market changes (i.e. changes in the market-specific markups). Explicitly, defining $r_{ij} = \frac{R_{ij}}{R_i}$ for parsimony, firm i's aggregate markup can be expressed as

$$\begin{aligned}\Delta\mu^L_{it} &= \mu^L_{it} - \mu^L_{it-1} \\ &= \sum_j r_{ijt}\mu^L_{ijt} - \sum_j r_{ijt-1}\mu^L_{ijt-1} \\ &= \sum_j \underbrace{r_{ijt}(\mu^L_{ijt} - \mu^L_{ijt-1})}_{\text{due to within-market changes in } j} \\ &\quad + \sum_j \underbrace{(r_{ijt} - r_{ijt-1})\mu^L_{ijt-1}}_{\text{due to reallocation toward market } j},\end{aligned} \tag{5}$$

where the final equality follows from adding and subtracting $\sum_j r_{ijt}\mu^L_{ijt-1}$.

3 Empirical application: the UK car market

3.1 Historical overview of the UK car market

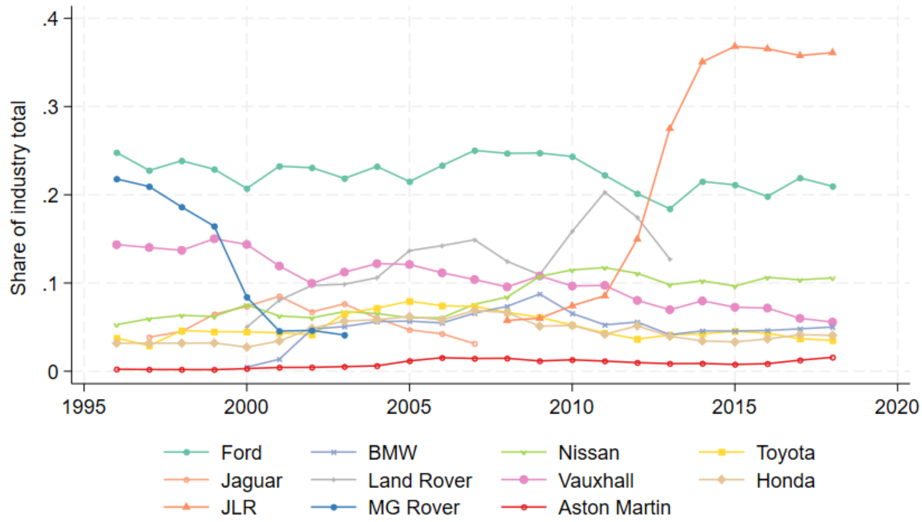
Both the supply- and the demand-side of the UK car market have undergone significant changes over recent decades.

Car manufacturing in the UK went through significant challenges during the 1970s such as labour strikes, financial difficulties, and increasing competition from international manufacturers. British Leyland, formed through the merger of several companies, struggled with inefficiencies and quality issues and was eventually nationalised in the 1980s. More positively, the 1980s marked the beginning of foreign investment in the UK with Japanese manufacturers such as Nissan and Toyota establishing production facilities to benefit from the UK's skilled workforce and strategic location within Europe. Foreign investment and ownership continued through the 1990s as Rover, formerly part of British Leyland, was sold to BMW, while American-owned Ford acquired the luxury brands Jaguar and Land Rover. The presence of Japanese manufacturers grew, with Honda joining Nissan and Toyota in setting up significant operations.

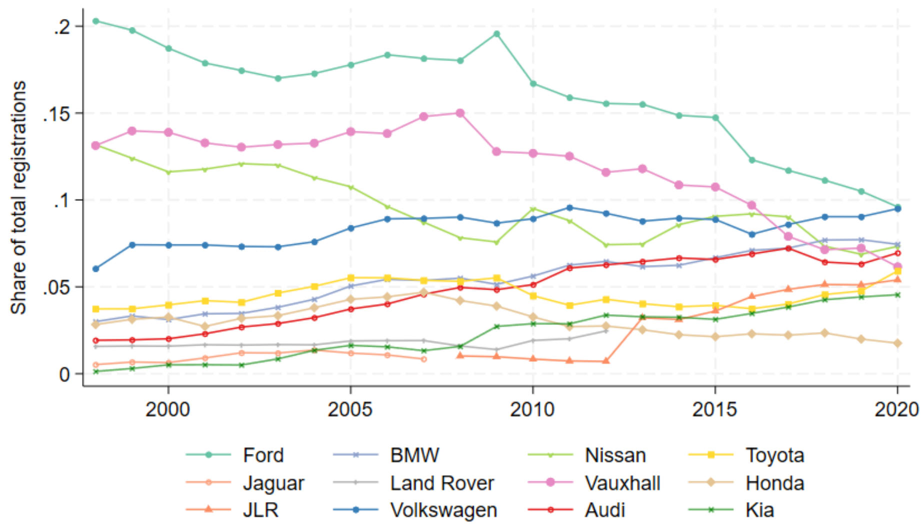
By the mid-1990s, when our production data begins, Ford accounted for approximately 25% of revenue in the industry with MG Rover representing just over 20% and Vauxhall 15%. Figure 1a shows MG Rover's market share fell sharply in the late 1990s and early 2000s as BMW sold off constituent brands retaining only Mini, which it revitalised under its own branding. Japanese manufacturers Toyota and Nissan increased their share of industry revenue during the early-mid 2000s but the largest change in the industry occurred in 2008 when Tata Motors acquired Land Rover and Jaguar. The newly-branded Jaguar-Land Rover (JLR) increased production dramatically over the following years, primarily via expansion into overseas markets. Land Rover became financially integrated into JLR in 2014 and by 2015 the combined company accounted for approximately 37% of industry revenue.

Figure 1: UK Car Market Shares

(a) Supply-side Revenue Shares



(b) Demand-side Registration Shares



Note: Figure 1a shows car manufacturing industry revenue shares of major brands. Figure 1b shows the share of all new annual car registrations accounted for by major brands. Series names pertain to distinct companies and do not reflect ultimate ownership.

Trends in UK car purchases have also undergone marked changes in recent decades as preferences have shifted away from UK-made cars while technological changes have seen different types of models enter the market. The 1980s and 1990s were characterised by a decline in the share of UK registrations accounted for by UK brands, with Japanese firms such as Nissan, Toyota and Honda rising in popularity as consumers favoured compact and mid-size vehicles. In the late 1990s, when our consumer data starts, Ford was the dominant brand, accounting for 20% of registrations with Vauxhall and Nissan each accounting for 13%. Preferences shifted toward luxury and performance vehicles in the early 2000s benefiting brands such as BMW and Audi, whose market shares rose from 2-3% in 2000 to around 5% in 2007. The financial crisis of 2008 affected sales briefly, but the market quickly rebounded. Ford and Vauxhall's popularity waned in subsequent years as consumers started to favour larger SUV models and South Korean brands, such as Kia.

Given the marked changes in composition, both on the supply- and demand-side of the UK car market shown in Figure 1, it is plausible that markups in the industry have also changed. We now examine this directly.

3.2 Markups in the UK car market

Consider a two-market application of equation 4, for a UK-based manufacturer which distinguishes the domestic (UK) market from the rest of the world (ROW). Expanding equation 4 for this simple example gives

$$\mu_i^L = \left(\frac{R_{iUK}}{R_i}\right)\mu_{iUK}^L + \left(\frac{R_{iROW}}{R_i}\right)\mu_{iROW}^L, \tag{6}$$

We use data from the UK car industry to demonstrate the utility of this simplified markup aggregation formula as a method of reconciling divergent trends in production and demand markup estimates. This section describes the data and methods used to calculate each component of equation 6.

3.2.1 Production markups

To obtain production markup estimates $\hat{\mu}_i^L$, we first estimate PMC markups using the methodology of De Loecker and Warzynski (2012) and use it to infer the Lerner Index as $\hat{\mu}_i^L = 1 - (1/\hat{\mu}_i^{PMC})$. De Loecker and Warzynski (2012) extend Hall (1988) to show that the first-order condition of a firm's cost minimisation problem taken with respect to a flexible input can be rearranged to obtain

$$\mu_i^{PMC} = \theta_i^X \frac{R_i}{C_i}.$$

We use Historical Orbis (HO) data on UK-based car manufacturers to implement this method.[4] HO data is derived from firms' financial documents and contains measures

4. Analysis is restricted to firms observed in the data used to estimate demand markups described in subsection 3.2.2. Although a subset of all UK-based car manufacturers, figure C.1 in appendix C.1 show these firms account for between 81 and 88 % of total annual revenue in the industry over our analysis period.

of input costs and revenue. Further data details, including sample summary statistics, are provided in appendix C. We take materials (defined as cost of goods sold minus the wagebill) to be our flexible input and assume the production technology is Cobb-Douglas as well as constant across firms and time. These assumptions impose $\theta_i^X = \theta^X$, which we estimate using variants on the log-linearised gross output production function:

$$y_{it} = \theta^0 + \theta^M m_{it} + \theta^W w_{it} + \theta^K k_{it} + \tau_t + \epsilon_{it}, \tag{7}$$

where y, m, w and k denote the log of revenue, materials, wagebill and fixed assets respectively. τ is a full set of year dummies and ϵ is an unobserved productivity shock.

Table 1: Production Function Estimates

	(1) OLS Levels	(2) OLS 1st diffs	(3) OLS FE Levels	(4) OLS Levels	(5) OP
Ln(Materials)	0.893***	0.919***	0.899***	0.891***	0.915***
	(0.052)	(0.076)	(0.062)	(0.053)	(0.046)
Ln(Wagebill)	0.066	0.092*	0.096**	0.061	0.038***
	(0.052)	(0.047)	(0.041)	(0.050)	(0.013)
Ln(Fixed Assets)	0.072	-0.029	0.075*	0.085	0.054***
	(0.046)	(0.029)	(0.038)	(0.048)	(0.006)
Year FEs	Yes	Yes	Yes	Yes	Yes
Firm FEs	No	No	Yes	No	No
N obs.	169	158	169	160	160
N firms	10	10	10	10	10

Note: standard errors in parentheses clustered at the firm level. */**/*** denote significance at the 10/5/1 percent level respectively.

Table 1 contains estimates of the input parameters of equation 7 obtained from various estimators. Column (1) contains estimates obtained via OLS estimation of equation 7. Columns (2) and (3) both contain OLS estimates on versions of equation 7 that are robust to fixed differences in productivity across firms: column (2) estimates equation 7 in first-differences, while column (3) estimates a version of equation 7 containing firm fixed effects. Column (4) repeats the method of column (1) on the sub-sample for which we observe investment, which is needed to implement the Olley-Pakes (OP) control function estimator (Olley and Pakes 1996), whose results are reported in column (5). Unlike the other estimates in the table, those in column (5) are robust to time-variant persistent productivity differences across firms, which the OP estimator controls for by assuming a monotonic relationship between persistent productivity and firms' investment decisions. While the wagebill and capital coefficients vary somewhat across methodologies, the materials coefficient is relatively stable and approximately equal to 0.9.[5] We therefore

5. Tables D.1-D.3 in appendix D summarise equivalent results obtained using dynamic panel estimation methods. In all cases, the coefficient on Ln(Materials) is approximately equal to 0.9

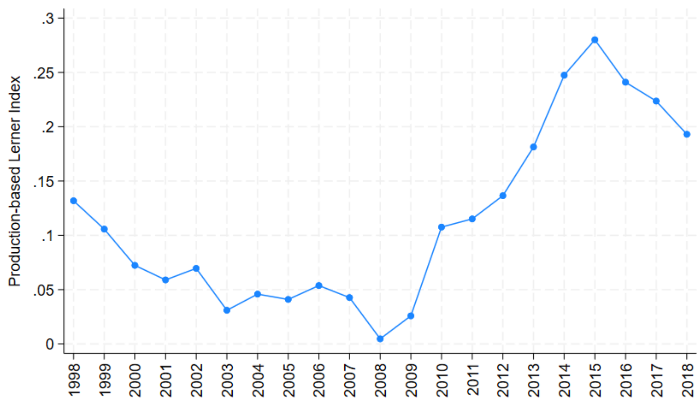
take 0.9 as our estimate of θ^M and estimate production markup as

$$\hat{\mu}_i^L = 1 - \frac{C_i}{0.9R_i},$$

where C is given as the cost of material purchases observed in HO.

Figure 2 shows mean production markups between 1998 and 2018.[6] Markups trended downward between 1998 and 2009, falling by over half from 0.14 to 0.03. They then jumped markedly to 0.1 in 2010 before increasing further to reach a peak of 0.28 in 2015. They declined slightly in the following years but, at 0.2 in 2018, are roughly 40% higher than at the beginning of the period.

Figure 2: Aggregate Production Lerner Index

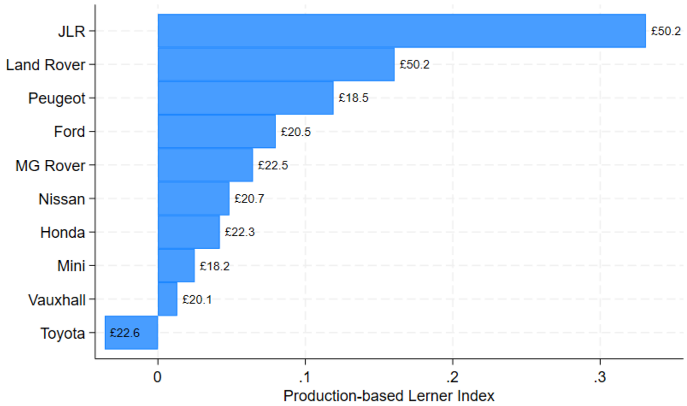


Note: figure shows the revenue-weighted mean production-based Lerner Index estimate. Series are restricted to car brands with manufacturing operations in the UK.

Figure 3 plots production markups by manufacturer, averaging across years. Jaguar-Land Rover (JLR), stands out as particularly high markup manufacturer, which is unsurprising given the average price of JLR models (denoted in bar labels). The high markup for Land Rover is similarly expected in light of the average price of their models but Peugeot is more surprising, having the third-highest markup and the lowest average price. This implies they are relatively productive and, indeed, the firm fixed-effect estimated via the OLS regression summarised in column (3) of table 1 is the highest among the manufacturers we consider.

6. To parallel our within-firm aggregation formula, the mean markup is calculated using revenue weights.

Figure 3: Aggregate Production Lerner Index By Manufacturer



Note: figure shows the revenue-weighted mean production-based Lerner Index estimate. Bar labels show the mean manufacturer-suggested retail price in thousands (deflated to 2018 prices), for models manufactured in the UK observed in the JATO data described in subsection 3.2.2.

3.2.2 Demand markups

We estimate UK demand markups using a range of approaches to model demand systems. This suite of estimators all require data on product attributes (most importantly price), and sales quantities. We obtain this data from JATO, a market intelligence company who collate data on registrations, manufacturer-suggested retail prices, and other attributes at the manufacturer-model-country of origin level. Our version of the JATO data cover all major manufacturers and account for approximately 95% of UK-based registrations over the period 1998-2022. We provide further details on data sources and construction in Appendix C.

Demand model

We consider the following demand system, closely following previous work in the demand estimation literature (e.g. Berry 1994; Berry et al. 1995). In the main specification of the paper we use a nested logit model.[7] In each year t, households i decide whether to buy car model $k \in [1...K]$ or choose the outside option (denoted $k = 0$). Models are partitioned into nests $b \in [1...B]$, such that models in the same nest are 'similar' in terms of their impact on consumer utility (conditional on characteristics). Households maximise their conditional indirect utility U_{ikt}:

$$U_{ikt} = \beta x_{kt} + \alpha p_{kt} + \xi_{kt} + (1 - \lambda)\zeta_{tb} + \lambda \epsilon_{ikt}, \tag{8}$$

7. We also estimated a random coefficient model following Berry et al. (1995). This gives us largely insignificant results which we attribute to relatively weak instruments and general problems with BLP-type demand estimation (Knittel and Metaxoglou 2014). We provide more details in Appendix E.

where x_{kt} denotes a vector of characteristics of model k in year t, p_{kt} is the price of model k in year t, ξ_{kt} is an unobserved demand shifter, ζ_{tb} is an unobserved component that is common across all alternatives in the same nest $b \in B$, and ϵ_{ikt} is a demand shock following a Type-1 extreme value distribution (i.i.d. across products).

Equation (8) yields a system of equations that we can solve analytically. Following Berry 1994 and making use of the Logit-property, we estimate

$$\log(s_{kt}) - \log(s_{0t}) = \beta x_{kt} + \alpha p_{kt} + (1-\lambda)\log(s_{kt|b}), \tag{9}$$

where s denote market shares, with s_{0t} the market share of the outside option in year t and $s_{kt|b}$ the share of model k in year t in nest b. Intuitively, the correlation parameter λ measures the the degree of substitutability within nests. We require $\lambda \in (0, 1]$ to be consistent with utility maximisation. Note that if the correlation parameter $\lambda = 1$, we are back to the multinomial logit model that does not account for correlation of tastes for unobserved characteristics within a nest. We define markets as respective years t and the market share of product k in market t as the number of sales divided by the number of UK households. The outside option s_{0t} (i.e. not buying a new car) accounts for the largest market share in all years of our sample (around 0.9).

From equation (9), we can derive expressions for own-and cross price derivatives for each product in each market. These measures of price sensitivity are, together with data on ownership, prices, and market shares, a key component to calculate product-level markups. Importantly, we need to distinguish between three different cases when calculating derivatives with respect to prices: formulas for the own-price derivative of product k, cross-price derivatives of product k with respect to the price of product r in the same nest, and cross-price derivatives of product r in a different nest. Price sensitivity in each of these cases is given as

$$\frac{\partial s_{kt}}{\partial p_{rt}} = \begin{cases} \alpha s_{kt}\left(\frac{1}{\lambda} - \frac{1-\lambda}{\lambda} s_{kt|b} - s_{kt}\right) & \text{if } r = k \\ -\alpha s_{rt}\left(\frac{1-\lambda}{\lambda} s_{kt|b} + s_{kt}\right) & \text{if } r \neq k, \text{but } r, k \text{ in same nest} \\ -\alpha s_{rt} s_{kt} & \text{otherwise.} \end{cases} \tag{10}$$

We calculate elasiticities with data on prices, market shares, and using parameter estimates of the price coefficient α and correlation coefficient λ.

To account for unobservable characteristics that are constant across time and models, we include market (i.e. year) and model fixed effects in all specifications. Formally, the error term with these fixed effects becomes

$$\xi_{kt} = \xi_k + \xi_t + \tilde{\xi}_{kt},$$

where ξ_k denote model fixed effects and ξ_t denote market fixed effects. Thus the identification assumption is that characteristics are uncorrelated with the part of the error term that is not controlled for with fixed effects, $\tilde{\xi}_{kt}$.

A well-known issue in estimating demand systems is the endogeneity of prices and market shares. Prices are likely to be correlated with unobserved product characteristics and demand shocks. To account for this, we require instruments that are correlated with prices, but uncorrelated with the error term $\tilde{\xi}_{jkt}$. First, we use the lagged price of aluminum multiplied with a model's weight as a price instrument. Intuitively, we can interpret this as a cost-shifter. Holding all else equal, an increase in the lagged price of aluminum should lead to a larger increase in prices for heavier cars, which require more input material for production. Second, we use the number of products within the same nest as an instrument for the within-nest market share $\log(s_{kt|b})$. Intuitively, more competition within the same nest should be associated with a lower market share of a given model within the nest.

We assign models to nests based on similiarities in their horsepower and weight. Using a k-clustering algorithm, we create four nests and ensure that a model is in the same cluster in different years of the sample.[8] We provide summary statistics of the different nests in Appendix C.

Estimation results

We show results from estimation of equation (9) in Table 2. Column (1) displays results from an OLS regression without instruments. Column (2) shows results from an IV regression using lagged aluminum prices multiplied with a model's weight as well as the number of products in the same nest as instruments. We include a model's horsepower-to-weight ratio (HP/W) and an indicator whether a model is observed for the first or last time in our data (to account for entry and exit) as characteristics.

The OLS regression serves as a valuable benchmark to evaluate the effectiveness of instrumental variables in the IV regression. The price coefficient α takes a value of -0.033 in the OLS regression. In the IV regression, the price coefficient α is about three times that magnitude and takes a value of -0.087 (statistically significant), suggesting more price-elastic demand. We could intuitively expect this shift as unobserved demand shocks correlated prices are likely to bias the price coefficient in the OLS regression. The coefficient on the within-nest market share λ is significant at the 5 percent level in the IV regression. The value of 0.2 suggests there is substantial substitutability between products within the same nest. We also observe that models with a higher horsepower-to-weight ratio (HP/W) are associated with a higher market share relative to the outside option, holding all other characteristics fixed. A model that appears for the first or last time in our data (In/Out Indicator) has a lower market share relative to the outside option, holding all other characteristics fixed.

Columns (3) and (4) show the two first-stage regressions corresponding to the IV regression. Looking at the first stage for the price variable in column (3), we observe that a higher value of the lagged aluminum price is associated with a higher market share relative to the outside option. Thus, the direction of the correlation of our instrument and the price variable is as expected. We can make a similar observation for the first

8. We also estimated a nested logit model with fewer and more nests, respectively. By going from three to four nests we obtain four nests that are notably different in terms of horsepower, weight, and prices. Adding a fifth nest yields two nest categories that are largely identical in terms of horsepower, weight, and prices. We therefore decided to use four nests.

stage of the log-market share within a nest. We observe that the larger the number of competing models within a nest, the lower the market share of a model within that nest, holding all else equal. F-Statistics of both first stages take values above 80.

Table 2: Nested logit estimation results

	(1) OLS	(2) IV	(3) 1st stage (price)	(4) 1st stage: Log(Share within nest))
Price ('000£)	-0.033**	-0.087***		
	(0.013)	(0.005)		
Log(Share within nest) (λ)	0.845***	0.196**		
	(0.018)	(0.095)		
HP/W	-5.549*	18.818***	322.897***	-2.433
	(3.098)	(6.280)	(69.009)	(1.507)
In/Out Indicator	-0.374***	-1.779***	-0.175	-2.171***
	(0.038)	(0.201)	(0.411)	(0.063)
Lagged alumninum price × Weight			0.013***	-0.001***
			(0.001)	(0.000)
# Products in nest			-0.107***	-0.027***
			(0.026)	(0.002)
Constant	-3.282***	-7.001***	-23.947**	-0.924**
	(0.371)	(1.128)	(12.075)	(0.447)
R^2	0.840	0.441		
Year FE	Yes	Yes		
Brand FE	Yes	Yes		
First Stage F			418	83
Observations	5590	5590	5590	5590

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: all columns include make fixed effects. Standard errors are clustered at the model level. Prices are deflated using the CPI and expressed in Thousands of 2018 GBP. 'HP/W' refers to a model's horsepower-to-weight ratio. 'In/Out Indicator' is a dummy variable that equals one if a model is observed the first or last time in our data and zero otherwise in order to account for entry and exit.

Supply-side and markup formula

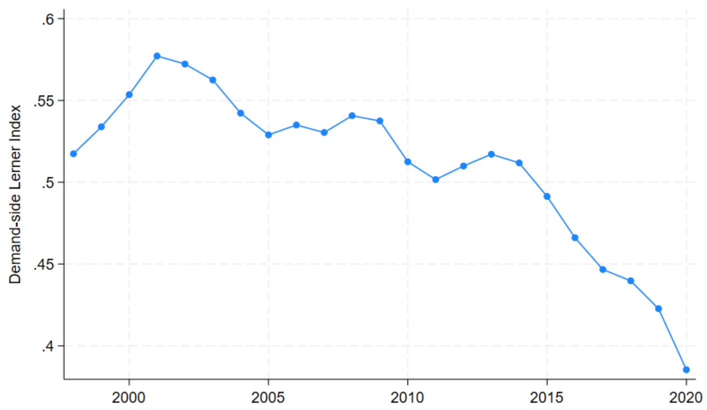
Estimates of our parameters α and λ combined with an assumption on market conduct let us identify markups. We assume that firms compete statically in prices under full information (Bertrand Nash competition is a standard assumption in the demand estimation literature, particularly in the application of cars, e.g. Berry et al. 1995; Grieco et al. 2023). Under this assumption, the first order conditions of firms imply the markup of model k in market t can (dropping time subscripts for convenience) be expressed as

$$\frac{p_k - c_k}{p_k} = \frac{[-\Omega(p)^{-1}s(p)]_k}{p_k}, \tag{11}$$

where c_k denotes the marginal cost of producing model k, and $s(p)$ are observed market shares. The matrix $\Omega(p)$ contains own-and cross-price derivatives with respect to models owned by the same firm in the same market.[9] We calculate these derivatives using results from our nested logit estimation and equation 10. We provide a full derivation of the markup formula in Appendix E.

Figure 4 shows the average revenue-weighted demand-side Lerner index over time. Two observations stand out. First, markups are relatively high in levels with the highest average markup in our sample period occurring in 2001 at around 0.57. Second, average markups have fallen over time from 0.51 in 1998 to 0.39 in 2020 - a fall of almost 30%.

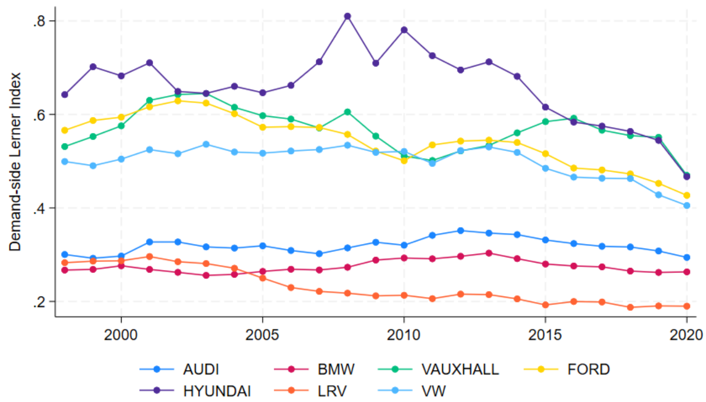
Figure 4: Aggregate Demand Lerner Index



Note: figure shows the average (revenue-weighted) demand Lerner Index.

9. We define ownership at the global level, i.e. we assume that the global owner rather than individual makes set prices. As an example, consider the Volkswagen group. We assume that the global owner, Volkswagen group, maximises profits of all its makes together (i.e. that of Audi, Skoda, Volkswagen, and others).

Figure 5: Aggregate Demand Lerner Index by Make



Note: figure shows demand-side Lerner index for selected makes, calculated as the revenue-weighted average over models.

Figure 5 shows the demand Lerner index for selected makes. Looking at changes over time, the graph suggests an overall decrease in markups for most makes over the sample period. Comparing markup levels across makes, we observe substantial differences compared with our production markup estimates shown below in Figure 3. On the one hand, the demand markup of Land Rover is lower than the markups of most other makes, with levels between 0.2 and 0.3. Vauxhall's demand markup is higher than most other makes, with levels over 0.6. Notable differences are eminent for other makes as well.[10]

3.2.3 ROW demand markups

Viewed together, the results of the preceding subsections may seem inconsistent: while production markups have doubled between 1998 and 2018, UK demand markups have fallen by almost half. One explanation for this inconsistency is that the assumptions made by either approach are invalid and hence the markup estimates are inconsistent. Alternatively, in light of the aggregation formula proposed in section 2, the divergence may be due to changes in the ROW demand markup.

To our knowledge, no existing work has attempted to quantify a ROW (i.e. 'export') demand markup. This is despite the work of De Loecker and Warzynski (2012) who find that production markups increase when firms start exporting, suggesting that the ROW demand markup differs from the domestic demand markup. If one had access to price and purchase data from all of the UK's major car export destinations, it would be possible to use our proposed aggregation formula to test the assumptions underpinning the production and demand markup estimators. Unfortunately this exceeds the resources of

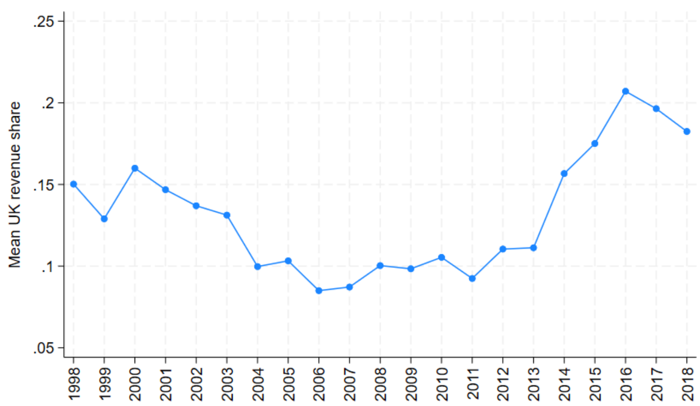
10. Note that we cannot compare demand and production markup estimates of all manufacturers/makes directly as some makes that sell in the UK have no UK production site and thus do not show up in our production data.

the current investigation. We instead assume that both production and demand markup estimation approaches are valid (i.e. we assume firms cost minimise and set prices according to static Bertrand Nash competition), to infer ROW demand markups and see how they can reconcile the divergent trends in production and UK demand markup estimates presented above.

Inferring ROW demand markups from UK demand and production markups requires export revenue at the firm level. We do not observe this directly but instead estimate it as the residual between UK car manufacturers' total revenues in a given year (observed in the HO data), and the product of price and quantity for the manufacturers' models that are manufactured and sold in the UK (observed in the JATO data), in that same year. While potentially subject to measurement error, for example due to inventory, we leverage additional data on exports from an industry organisation and show in appendix figure F.1 that our estimated export revenue shares align closely with export quantity shares.

Figure 6 plots the mean UK revenue share over time. After rising from 0.2 in 1998 to 0.25 in 2000, the share of UK car manufacturers' revenue obtained from UK sales fell to 0.15 in 2004. It remained at this level until 2013 before increasing steadily back up to 0.2 in 2016. Throughout the period, therefore, UK sales accounted for a small portion of revenue obtained by UK car manufacturers suggesting their markups are predominantly determined by demand conditions beyond the UK.

Figure 6: UK revenue share



Note: figure shows mean UK revenue shares calculated by inferring UK revenue from JATO data and taking total revenue from HO.

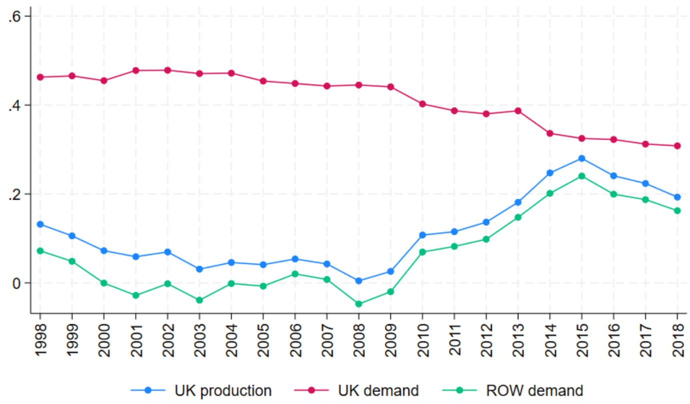
Equipped with the revenue share estimates, we can invert equation 6 to infer the ROW Lerner-index markup as

$$\hat{\mu}_{iROW}^{L} = \frac{R_i}{\hat{R}_{iROW}} \left(\hat{\mu}_i^L - \left(\frac{\hat{R}_{iUK}}{R_i} \right) \hat{\mu}_{iUK}^L \right). \tag{12}$$

This equality allows us to calculate the ROW markup required to reconcile production and UK demand markup estimates. Although arguably uninteresting on its own, we can corroborate the implied trend in ROW demand markups using supplementary data to verify whether the implied trends are plausible.

Figure 7 plots estimates of the Lerner Index markup using the UK production, UK demand methods described in the preceding subsections and ROW demand method outlined above. The contrast between the UK production and UK demand markups is stark when viewed together: the UK demand markup is more than three times as large at the beginning of the period and declines while the UK production markup increases. The ROW demand series shows what one must believe has happened to markups obtained by UK-based firms on their exports for both UK markup series to be consistent. Between 1998 and 2009 ROW demand markups were essentially zero and even turned negative in the early 2000s.[11] Since 2009 they have risen markedly in a manner that largely parallels the increase in the UK production markup, albeit more remarkable given the lower starting value.[12]

Figure 7: Aggregate Lerner Index Markups



Note: figure shows revenue-weighted mean markup estimates. Series are restricted to car brands with manufacturing operations in the UK.

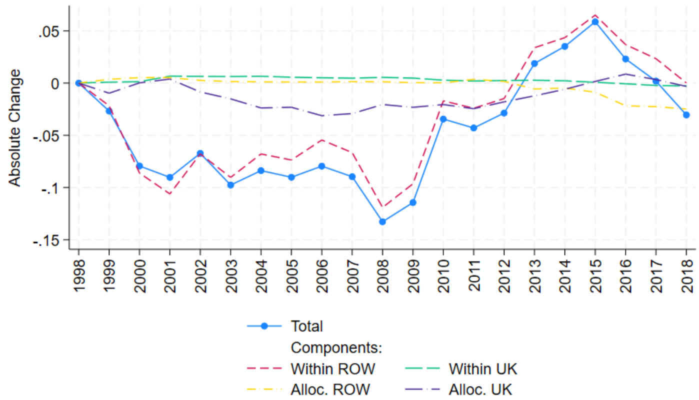
To what extent have changes in demand markups within markets and changes in market shares driven the UK production markup? To shed light on this question, Figure 8 implements the decomposition of equation 5, distinguishing between the UK and ROW markets. The figure plots the total cumulative change since 1998 in the UK production markup alongside the cumulative changes in the within and between market components.

11. The negative Lerner Index markup implies firms were losing money on exports, which could be rationalised by firms running losses in order to enter new markets.

12. The close co-movement between the UK production and ROW demand markups is a consequence of the low UK revenue share shown in figure 6, which implies the UK production estimate is primarily composed of the ROW demand estimate.

This shows the increase in the UK production markup over the period is entirely due to within-market increases in the ROW markup. This increase is partially offset in the middle of the analysis period by decreases in the share of output sold within the UK (where demand markups are higher), and by the reduction in the UK demand markup.[13]

Figure 8: Change in Aggregate Production Lerner Index



Note: figure shows the cumulative absolute difference in the revenue-weighted mean producer-side Lerner markup estimate and its components.

In summary, if our estimates of both UK production and UK demand estimates are unbiased, their divergent trends can be reconciled by a marked increase in the ROW demand markup. In the following section we leverage administrative trade data to gauge whether such an increase is plausible.

3.3 Export patterns and markups

Our examination of the ROW demand markup thus far has been triangulation: given the UK demand markup, the UK production markup and the share of revenue UK manufacturers' gain from domestic sales, ROW demand markups can be inferred under the assumption that our estimates of UK production and UK demand markups are unbiased. If this is the case, figure 8 shows that markups gained by UK car manufacturers on their exports increased markedly between 2009 and 2018. If the destination of UK car exports remained unchanged over our analysis period, such a large increase in the markup obtained on exports would appear implausible as it would require a considerable change in within-country preferences. Trade data can therefore provide evidence that

13. Note that we focus on changes rather than levels in this decomposition analysis. Because we use revenue data to estimate production-side markups, a worry is that the level estimates might be biased (Bond et al. 2021). However, De Ridder et al. (2024) show that trends in production-side markup estimates are identified with revenue data. Thus, our main results is about differences in trends rather than levels of the two markup series, as depicted in Figure 8.

corroborates or challenges the conclusions of our markup analysis.[14]

We first use administrative data on trade patterns to characterise the relationship between production markups and particular export markets. Combining firm financial data from the Annual Business Survey (ABS)[15], with customs data on goods exports known as the Trade in Goods (TIG)[16] data allows us to relate firm-level markups to export revenue shares distinguishing between countries.[17] We focus on the several salient export markets and estimate the following specification on the sample of UK car manufacturers

$$\hat{\mu}_{it} = \beta_0 + \beta_1 r_{itCN} + \beta_2 r_{itUS} + \beta_3 r_{itEU} + \beta_4 \mathbb{I}[X_{it}] + \tau_t + \epsilon_{it} \tag{13}$$

where $r_{itCN/US/EU}$ are Chinese/US/EU export revenue shares defined as firms' value of exports to the specific destination divided by revenue. $\mathbb{I}[X_{it}]$ is an indicator function that takes the value of 1 if a firm exports and zero otherwise, and all other is as before.

Table 3: Markups and Export Markets

	(1)	(2)	(3)	(4)	(5)	(6)
China turnover share	0.447***	0.427***	0.629	0.457*	0.329**	1.805***
	(0.127)	(0.143)	(0.414)	(0.245)	(0.146)	(0.526)
US turnover share	0.318***	0.313***	0.472	0.094	0.055	1.026***
	(0.104)	(0.110)	(0.391)	(0.147)	(0.136)	(0.386)
EU turnover share	-0.075*	-0.083	0.072	-0.076	-0.130	0.868**
	(0.042)	(0.061)	(0.361)	(0.131)	(0.099)	(0.365)
Exporter dummy	-0.113***	-0.150	-0.113***	-0.061	-0.984***	-0.035
	(0.036)	(0.119)	(0.036)	(0.040)	(0.358)	(0.039)
Ln(Exports)		0.002			0.053***	
		(0.006)			(0.020)	
Exports/Turnover			-0.115			-0.735***
			(0.300)			(0.265)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Firm FEs	No	No	No	Yes	Yes	Yes
N obs.	387	387	387	387	387	387
N firms	107	107	107	107	107	107

Note: standard errors in parentheses clustered at the firm level. */**/*** denote significance at the 10/5/1 percent level respectively. Estimates weighted by turnover.

Table 3 summarises OLS estimates of the baseline specification 13 and various extensions. Columns (2) and (5) additionally control for the value of total exports (in logs), while columns (3) and (6) control for total exports as a share of revenue. Columns (4) to (6) estimate similar specifications to columns (1) to (3) respectively but additionally control for firm fixed effects. The estimates across all specifications show that exporting

14. If it were possible to match our UK demand markup estimates to administrative firm data, one could decompose the ROW demand markup into country-specific components. We are unable to do so since the data used to estimate UK demand markups lacks the anonymous firm identifiers required for administrative data matching.

15. Office for National Statistics (2023) and Office for National Statistics (2024).

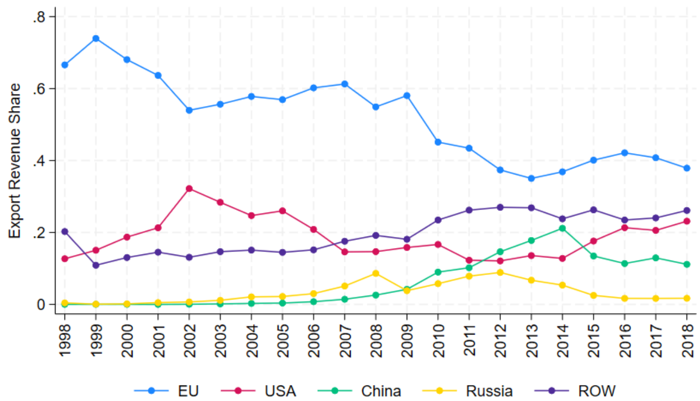
16. Office for National Statistics (2022).

17. Further details on both datasets and descriptive statistics are provided in appendix C.

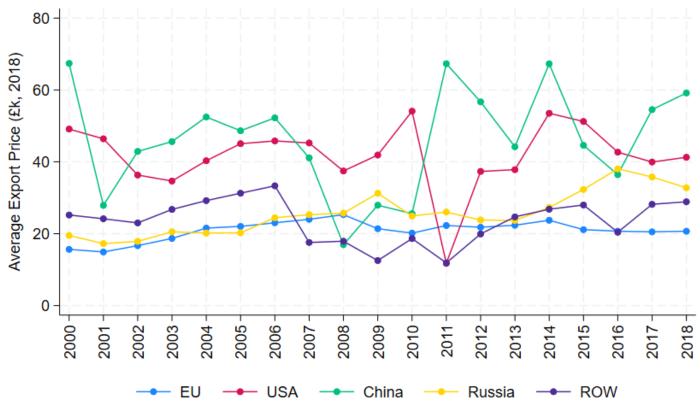
to China and to the US has a positive significant impact on car manufacturers' markups of greater magnitude than exporting to the EU. The relative insignificance of exports to the EU is likely due to EU competition regulation, which sought to reduce price differentials in similar automotive products across member states.[18] Controlling for firm fixed effects shows that deviations in markups from within-firm means are particularly driven by exports to China.

Figure 9: Export Characteristics

(a) Export Markets



(b) Average Prices



Note: figure 9a shows shares of total UK car export revenue by destination. Figure 9b shows average prices of UK car exports by destination, calculated as the value of exports divided by the number of units exported. Cars identified as HS code 8703 'Motor cars and other motor vehicles principally designed for the transport of <10 persons'. Data from UN Comtrade.

The results in Table 3 show firms' markups vary according to where they sell their

18. For example see the EU Commission's competition policy documents on motor vehicles,

output suggesting that consumer preferences differ across export markets. Given the large positive association between firm-specific markups and exports to China and the US, expanding into these markets may explain the large increase in the ROW demand markup shown in section 3.2.3. Figure 9a shows these are exactly the export markets that have grown since 2009, which is the period during which the ROW demand markup increased, Figure 9b shows average prices of exports to these markets are considerably higher than exports to the EU and have increased, albeit noisily, since 2009. These results corroborate the increase in the markup gained by UK car makers on their exports shown in Section 3.2.3, suggesting this increase is due to expansion into China and the US, both relatively high markup markets.

4 Conclusion

Demand-based and production-based approaches to markup estimation require different types of data and impose different assumptions. Demand-based approaches specify consumers' choice process and firms' pricing behaviour whereas production-based approaches assume cost minimisation and input flexibility. This paper shows that demand- and production-based markup estimates can diverge when firms sell in multiple markets, even if both sets of assumptions hold. To clarify this point, we derive an aggregation formula that shows producer-based markups can be expressed as a revenue-weighted mean of market-specific markups. This aggregation has practical advantage over the cost share-based aggregations derived by De Loecker and Warzynski (2012) and Ciarncross et al. (2023), as market revenue shares are more easily observed than market cost shares, which often require additional assumptions on firms' production technology.

We demonstrate the utility of this aggregation formula in the context of the car market - an industrial context that has long been a laboratory for markup estimation. While we find demand-based markups have fallen between 1998 and 2018, production markups have increased due to an increase in the markups that UK car manufacturers gain on their exports. We corroborate this finding using administrative trade data, which suggests expansion into China has driven the increase in production-based markups.

Our theoretical and empirical results show demand-based and production-based markups are conceptually different quantities in the presence of trade. An important avenue for future work would be to use demand-data across multiple export markets, so country-specific elasticities and markups could be estimated.

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A Price-marginal cost ratio aggregation

Now consider price-marginal cost (PMC) markups

$$\mu_{ijk}^{PMC} = \frac{p_{ijk}}{c_{ijk}}, \tag{14}$$

where all notation is as before.

As noted by De Loecker and Warzynski (2012) and Ciarncross et al. (2023), one can express aggregate firm-level PMC markups as a *cost share*-weighted average of market or product-specific PMC markups (De Loecker and Warzynski (2012) focus on aggregation across markets, while Ciarncross et al. (2023) focus on aggregation across products). However, this requires data on the distribution of aggregate firm costs across goods or markets, which is not typically available. Alternatively, one can also express aggregate PMC markups as a revenue-weighted function of model-market PMC markups.

For conciseness, we drop the subscript k and ignore aggregation across goods.[19] As De Loecker (2011) highlights, firm i's PMC markup can be expressed as

$$\mu_i^{PMC} = \theta_i^X \frac{R_i}{C_i}, \tag{15}$$

where θ_i^X denotes the output elasticity of a perfectly variable input X for firm i.[20] This can be interpreted as a revenue-weighted function of μ_{ij}^{PMC} since

$$\begin{aligned}
\mu_i^{PMC} &= \theta_i^X \frac{R_i}{C_i} \\
&= \theta_i^X R_i \left(\sum_j C_{ij}\right)^{-1} = \left(\frac{1}{\theta_i^X R_i} \sum_j C_{ij}\right)^{-1} \\
&= \left(\sum_j \frac{R_{ij}}{R_i} \frac{C_{ij}}{\theta_i^X R_{ij}}\right)^{-1} = \left(\sum_j \frac{R_{ij}}{R_i} \frac{1}{\mu_{ij}^{PMC}}\right)^{-1},
\end{aligned} \tag{16}$$

where the final equality makes the assumption that the output elasticity of a static input

19. The approach to aggregating across goods is analogous to aggregating across markets, as demonstrated in sub-section 2.

20. More precisely, 'perfectly variable' in this context means an input subject to zero adjustment costs and which can therefore be optimised period-by-period. Conditional on other dynamic inputs, such as capital, this allows one to ignore dynamic aspects of a firms' cost-minimisation problem, which leads to the neat closed-form markup expression of equation 15.

X is the constant across markets.[21] Inverting the LHS of equation (16) gives

$$\frac{1}{\mu_i^{PMC}} = \sum_j \frac{R_{ij}}{R_i} \frac{1}{\mu_{ij}^{PMC}}, \tag{17}$$

which shows the inverse of a firm's PMC markup can be expressed as a revenue-weighted average of the inverse of their market-specific PMC markups. Although less straightforward than the Lerner-index aggregation, it is reassuring that one can express both Lerner-index and PMC markups as revenue-weighted averages of market-specific markups.

B Non-constant marginal costs

The derivations in the main text assume marginal costs are constant with respect to the quantity produced, i.e. $MC(q) = \bar{c}$. This assumption implies the Cost of Goods Sold (COGS) can be written as the product of quantity and marginal cost ($COGS = q \cdot \bar{c}$). Accordingly, with constant marginal costs, markups can be directly computed from the observation of revenue and COGS.[22] The markup estimation approach of De Loecker and Warzynski (2012) does not require this assumption. Instead, marginal costs are treated as unobserved and markups are backed out structurally from the estimated production function in combination with assuming cost-minimising firm behaviour. In this appendix, we show that we can derive a similar markup aggregation formula as in the main text in the case of non-constant marginal costs.

For simplicity, focus on the case where the firm sells a product either into domestic or foreign markets. The quantity sold is q^D for the domestic market and q^F for the foreign market. Similarly, the price differs between markets and is denoted as p^D and p^F. Firms produce the total quantity $q = q^D + q^F$ and the marginal cost of producing an additional unit is $c = MC(q)$. The average price which the firm obtains on its sales its $p = \omega^D p^D + \omega^F p^F$, where $\omega_D = \frac{q^D}{q}$ is the fraction of the quantity which is sold in the domestic market (similarly for ω_F). The revenue which the firm receives in market k is $R^k = p^k q^k$ and total revenue is $R = R^D + R^F$.

The aggregate markup from the perspective of the firm compares the average price it achieves on its sales with the cost of producing an additional unit:

$$\mu = \frac{p-c}{p} = \frac{\omega^D p^D + \omega^F p^F - c}{\omega^D p^D + \omega^F p^F}$$

21. This assumption may be violated if, for example, there were substantial variation in quality across markets or if firms manufactured multiple products, each with different output elasticities, and sold products in different ratios across markets.

22. Since revenue is the product of quantity and price ($R = q \cdot p$), the ratio of COGS and revenue gives the price-cost margin with constant marginal costs ($\frac{R}{COGS} = \frac{p}{c}$).

This expression can be rearranged:

$$
\begin{aligned}
\mu &= \frac{\omega^D p^D + \omega^F p^F - c}{\omega^D p^D + \omega^F p^F} \\
&= \frac{\omega^D p^D + \omega^F p^F - \omega^D c - \omega^F c}{\omega^D p^D + \omega^F p^F} \quad \text{(using } c = \omega^D c + \omega^F c\text{)} \\
&= \frac{\omega^D p^D - \omega^D c}{\omega^D p^D + \omega^F p^F} + \frac{\omega^F p^F - \omega^F c}{\omega^D p^D + \omega^F p^F} \\
&= \frac{q^D p^D - q^D c}{q^D p^D + q^F p^F} + \frac{q^F p^F - q^F c}{q^D p^D + q^F p^F} \quad \text{(multiplying by } \frac{q}{q}\text{)} \\
&= \frac{q^D p^D - q^D c}{R} + \frac{q^F p^F - \omega^F c}{R} \\
&= \frac{R^D}{R^D}\frac{q^D p^D - q^D c}{R} + \frac{R^F}{R^F}\frac{q^F p^F - q^F c}{R} \\
&= \frac{R^D}{R}\frac{q^D p^D - q^D c}{R^D} + \frac{R^F}{R}\frac{q^F p^F - q^F c}{R^F} \\
&= \frac{R^D}{R}\frac{p^D - c}{p^D} + \frac{R^F}{R}\frac{p^F - c}{p^F} \\
&= \frac{R^D}{R}\mu^D + \frac{R^F}{R}\mu^F
\end{aligned}
$$

μ^D is the domestic markup, which compares the domestic price of a unit (p^D) to the marginal cost of producing an additional unit ($c = MC(q)$) and similarly μ^F is the foreign markup. Like in the main text, the aggregate markup is the revenue-weighted sum of these market-specific markups.

C Data

C.1 Historical Orbis

Historical Orbis (HO) includes data on active and dead incorporated firms in various corporate databases constructed by Bureau Van Dijk (BVD). These databases compile accounting information on firms as well as attributes such as location and industry from corporate documents such as annual reports and account filings. The UK component of this is FAME and spans several decades. An earlier iteration of FAME, known as Amadeus, included observations on some notable UK car manufacturers which - for reasons unclear to the authors - are absent in the latest data. We therefore combine HO with Amadeus in an effort to improve the coverage of our corporate financial data.

HO often contains multiple observations per firm-year pertaining to different information sources. We obtain a single observation per firm-year by prioritising information from annual reports over local registry filings, information filed at the end of a month rather than the beginning and consolidated over unconsolidated accounts. We harmonise data to account for differences in reporting period length and span by assuming values are distributed uniformly across months in a given period, This allows us to expand the reporting periods into a monthly panel, which we use to construct observations at the calendar year-firm level.

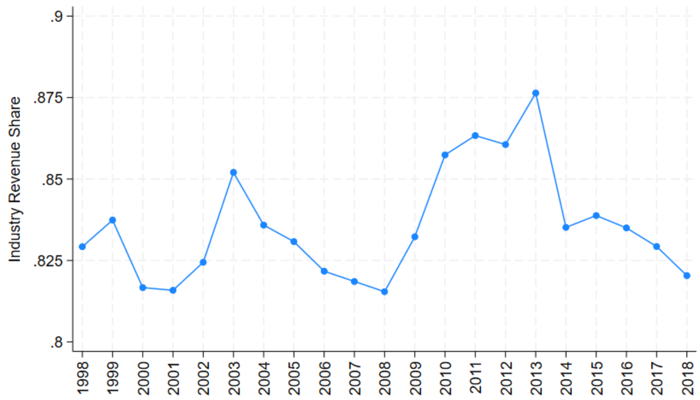
HO contains multiple industry codes per firm to reflect a range of their activities. We classify firms as car manufacturers if *any* of their associated NAICS codes are recorded as 336111 ('Automobile Manufacturing'). Our analysis sample is restricted to car manufacturers that are observed in the JATO data. Table C.1 shows the characteristics of this sample compared to all car manufacturers observed in HO. The average firm in our analysis sample is clearly far larger than the average car manufacturer observed in the UK, which is due to the JATO data being restricted to car manufacturers with non-negligible shares of the UK market. Figure C.1 shows that these firms account for the vast majority of revenue in the industry.

Table C.1: Historical Orbis Descriptive Statistics

	UK Car Manufacturers					
	All			Analysis Sample		
	Mean	Median	S.D.	Mean	Median	S.D.
Revenue (£bn)	0.43	0.01	2.01	6.81	4.59	5.71
Employment (ths)	0.6	0.1	2.4	7.4	4.6	7.2
Wage bill (£bn)	0.06	0.01	0.24	0.60	0.35	0.64
Material Inputs (£bn)	0.58	0.02	1.91	5.42	3.97	3.63
Fixed assets (£bn)	0.04	0.00	0.50	1.96	0.99	3.19
EBITDA (£bn)	0.01	0.00	0.20	0.21	0.12	0.80
N Obs.		13873			167	
N Firms		1962			10	

Note: monetary values are deflated using the CPI and expressed in 2018 prices.

Figure C.1: Revenue Share of Sample Manufacturers



Note: figure shows the share of total revenue among UK car manufacturers accounted for by manufacturers in our analysis sample.

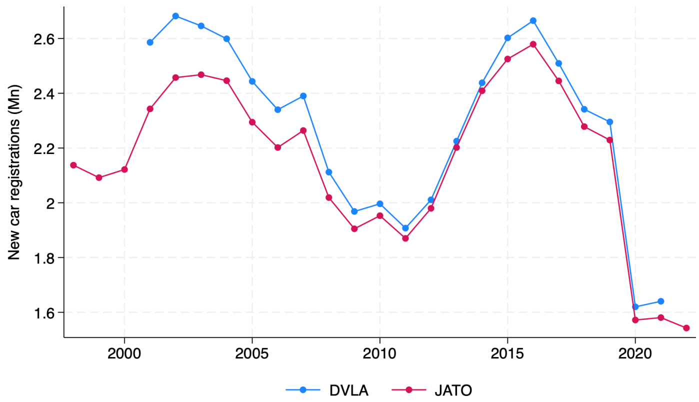
C.2 Demand-side data

Our primary source of demand-side data was obtained from JATO, a market intelligence firm. This data includes price, weight, horsepower, sales and number of trims at the year-make-model-country of assembly level. The data provided is averaged across number of trims (a model can be sold in different versions, referred to as *trim*), weighted according to trim-specific sales.

The measure of price observed in the JATO data is the price suggested by the manufacturer incl. VAT. We thus do not observe actual transaction prices, i.e. those that include potential discounts granted by dealers. For newly introduced models, we do not observed the month of first listing. Similarly, for models that stopped being sold, we do not observe the exact month a model is taken out of the market. This may cause a problem if entering/exiting firms have a low market share because they were not sold for an entire year. We aim to account for this potential problem by including a dummy variable indicating the first/last time a model is observed.

We complement the JATO registration data with various other data. These include: Consumer Price Index (CPI) data from ONS, data with the aggregate number of households in the UK by year from ONS, data on real exchange rate relative to the US in different countries from Penn World Tables (PWT), average annual aluminium price data from St. Louis FED (FRED), and UK income data from the Family Resources Survey (FRS).

Figure C.2: Number of Registrations



Note: Number of registrations by year published by UK Driver and Vehicle Licensing Agency (DVLA) compared with JATO data. DVLA data only available 2001 onwards.

Figure C.2 compares the number of registrations observed in the JATO data with official data published by the UK Driver and Vehicle Licensing Agency (DVLA). We observe a slight discrepancy at the beginning of the time period, but numbers and trends are very similar. The slight discrepancy arises because JATO provides us with data of models that are within the top in 90% of sales in at least one year of the time period (i.e. if a model is within the top 90% in 2005 but in no other year, it will show up in the data for all years of the time period 1998-2022).

Table C.2 shows summary statistics of our sample. The number of brands have stayed relatively constant, registrations fluctuate with the business cycle, and the shares of cars produced in Great Britain and the European Union have decreased, respectively. Average real prices have seen an increase over time as well as the observed average horsepower to weight ratio.

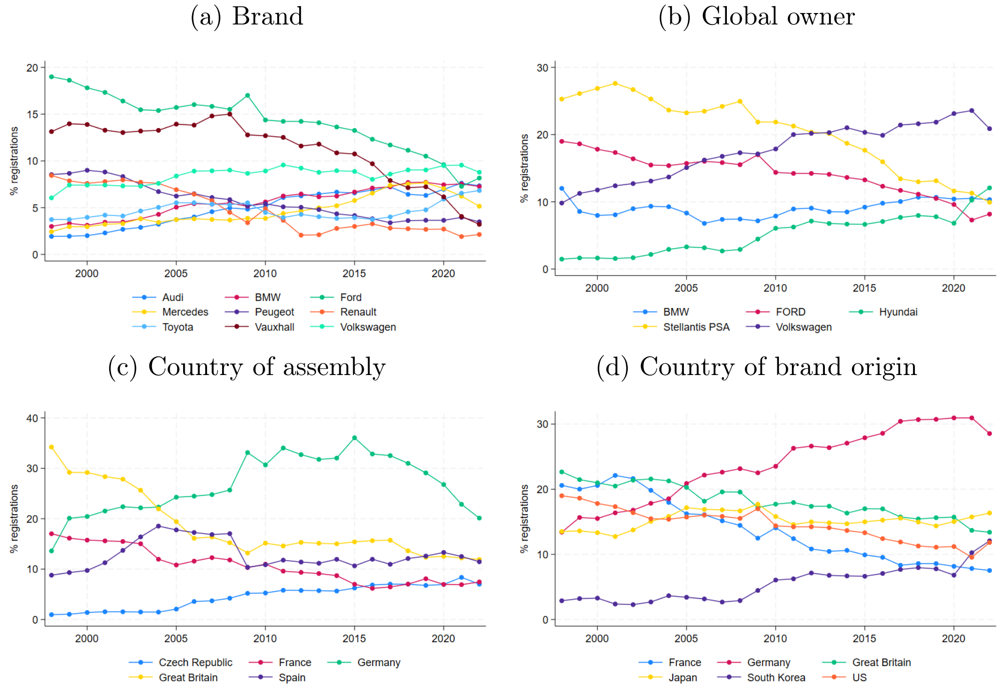
Table C.2: Descriptive Statistics of Demand Data

Year	Models	Brands	Registrations	GB produced	EU produced	GB brand	Price	HP/W	Trims
1998	173	25	2.123	0.34	0.89	0.23	21.159	0.084	9.96
1999	179	25	2.083	0.29	0.88	0.21	20.868	0.085	9.38
2000	193	25	2.100	0.29	0.90	0.21	20.152	0.085	9.05
2001	197	26	2.332	0.28	0.91	0.20	19.376	0.086	9.25
2002	200	26	2.443	0.28	0.91	0.21	19.623	0.087	8.64
2003	204	26	2.449	0.26	0.89	0.22	20.129	0.086	8.44
2004	210	26	2.385	0.22	0.86	0.21	20.878	0.086	8.58
2005	213	26	2.211	0.19	0.86	0.20	21.482	0.086	9.00
2006	220	25	2.128	0.16	0.87	0.18	21.591	0.087	8.49
2007	227	25	2.204	0.16	0.90	0.20	21.735	0.089	8.45
2008	233	24	1.988	0.15	0.90	0.20	21.154	0.089	8.69
2009	240	24	1.859	0.13	0.88	0.17	21.057	0.088	8.86
2010	240	25	1.946	0.15	0.88	0.18	22.132	0.089	8.61
2011	234	25	1.866	0.15	0.89	0.18	22.623	0.091	9.45
2012	248	25	1.973	0.15	0.88	0.17	22.342	0.091	9.30
2013	250	25	2.199	0.15	0.88	0.17	22.161	0.092	9.45
2014	250	26	2.386	0.15	0.88	0.16	22.485	0.093	9.14
2015	255	26	2.507	0.15	0.88	0.17	23.541	0.096	9.90
2016	254	26	2.571	0.16	0.86	0.17	24.829	0.099	9.69
2017	251	26	2.422	0.16	0.85	0.16	25.827	0.101	9.90
2018	254	26	2.236	0.14	0.84	0.15	26.211	0.103	9.29
2019	262	26	2.200	0.12	0.84	0.16	27.053	0.104	9.48
2020	243	26	1.550	0.13	0.83	0.16	29.047	0.109	9.21
2021	245	26	1.540	0.12	0.79	0.14	29.895	0.111	9.02
2022	251	26	1.495	0.12	0.75	0.13	29.604	0.114	7.91

Note: columns 2 to 4 show count by year in each cell. Columns 5 to 7 show the share of registrations produced in GB/EU and the share of registrations from GB brands. Columns 8 to 10 show registration weighted means in each cell. Registrations are shown in Millions and Price in Thousand pounds deflated to 2018 price level. HP/W refers to the horsepower to weight ratio. A car is classified as EU produced if the country of assembly was a member of the EU in at least one year over the entire sample period (e.g. Croatia only joined the EU in 2013, but cars produced in Croatia prior to 2013 are classified as EU produced). GB brand refers to the share of cars produced by firms with British origin, e.g. Vauxhall (although Vauxhall is owned by a foreign company).

Figure C.3 shows additional trends in the data over time. The four panels show the market shares by brand, global owner, country of assembly, and country of brand origin for our sample period.

Figure C.3: Market Shares



Note: figures show selected brands/countries (lines do not add up to %). Country of assembly is a variable provided by JATO. Country of brand origin is self-coded. For example, Vauxhall is coded as British, Volkswagen as German, and Skoda as Czech (note that it is about the origin of the brand, not about ownership or production).

UK revenue shares are inferred from JATO data by selecting models that are recorded as UK-made and calculating UK revenue = MSRP*Volume. The following makes in the JATO data are combined as they appear under one manufacturer in the UK data.

- Renault is combined with Nissan as they operate as a single entity known as the 'Renault-Mitsubishi Alliance'.
- Mazda is combined with Ford as the latter owned the former in the years that Mazda is observed as UK-made (1998-2002).
- Land Rover is combined with Jaguar from 2013 onwards as Land Rover's revenue as recorded in HO is negligible after this date.
- MG is combined with Rover during its years of operation, as the two manufacturers were co-owned during their years of operation (1998-2004).

C.3 Annual Business Survey

The Annual Business Survey (ABS) is an annual survey conducted by the Office for National Statistics and regarded as the principal source of UK business data. Before

2009, it was referred to as the Annual Business Inquiry – part 2 (ABI/2), with historical data stretching back to 1995 for the entire economy and to 1980 for manufacturing.

The ABS collects information on key financial metrics including turnover, purchases, employment costs and capital expenditure from companies in the UK's non-financial business sector, which constitutes roughly two-thirds of the entire UK economy. Approximately 62,000 businesses across Great Britain and approximately 11,000 businesses in Northern Ireland are sampled from the UK's Inter-Departmental Business Register (IDBR), which includes information on companies registered for Value Added Tax (VAT) and employee tax, as well as incorporated businesses registered at Companies House. The IDBR includes around 2.6 million businesses accounting for nearly 99% of UK economic activity although it excludes the self-employed without employees not registered for employment tax, companies with minimal turnover not registered for VAT, and some non-profit organizations. The ABS utilizes a stratified random sample design with sampling strata based on employment size, industry code and geographical region. Firms with at least 250 employees are sampled every year smaller firms sampled on a rolling basis such that a firm is generally selected for a two-year period andis then unlikely to be re-selected for at least another two years.

ABS questionnaires are sent to business entities known as 'reporting units'. For most businesses, the reporting unit is typically the legal entity that has been registered for VAT and/or employment tax, or the incorporated entity registered at Companies House. In large, complex businesses or conglomerates that consist of multiple operations or divisions, the reporting unit might be a specific part of the business that is responsible for its own financial transactions and records. Reporting units are assigned a single industry code according to the activity that generates the majority of their revenue. We classify firms as car manufacturers if this code is recorded as Standard Industrial Classification code 2901 ('Manufacture of motor vehicles'). Although the manufacture of parts and accessories for motor vehicles are recorded under a different industry code, it should be noted that SIC 2901 spans more than the manufacture of finished vehicles, including operations such as the manufacture of vehicle engines and chassis.

We combine the ABS with the Trade in Goods data described below to measure firms' revenue and relate export revenue shares to production markups, estimated using the formula outlined in section 3.2.1. Summary statistics of our analysis sample are provided in the following subsection.

C.4 Trade in Goods

Trade in Goods (TIG) is administrative data drawn from trade declarations submitted to HMRC, the UK's tax authority aggregated to the firm-country-product-flow-year level. Prior to the UK's departure from the European Union in 2020, trade with EU member countries only had to be reported if the annual value of flows was above a certain threshold. These thresholds apply to imports and exports separately and have changed over time starting at £225k for both imports and exports at the start of the sample period in 2005 but diverging subsequently with the threshold for imports increasing by far more than the threshold for exports. In 2019, the threshold for reporting imports was £1.5mn while for exports it was £250k. This means the coverage of exports to the EU will be more comprehensive than the coverage of imports from the EU in later years. Trade flows to and from non-EU countries are reported irrespective of value.

We match TIG and the ABS using unique reporting unit identifiers and use the TIG information to calculate export revenue shares. Summary statistics of our analysis sample are provided in table

Table C.3: Annual Business Survey-Trade in Goods Descriptive Statistics

	2005-2019		2005-2009		2010-2014		2015-2019	
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Production Markup	1.10	0.14	1.10	0.14	1.09	0.15	1.09	0.13
Exporter Dummy	0.91	0.28	0.93	0.26	0.93	0.25	0.88	0.32
Ln(Exports)	15.73	5.88	15.60	5.49	16.52	5.42	15.22	6.44
China Export Turnover Share	0.02	0.05	0.01	0.02	0.03	0.07	0.02	0.04
US Export Turnover Share	0.05	0.12	0.04	0.08	0.04	0.10	0.06	0.15
EU Export Turnover Share	0.14	0.15	0.14	0.16	0.15	0.16	0.12	0.14
N obs.	430	430	129	129	130	130	171	171

Note: sample restricted to car manufacturers identified as SIC code 2901. Statistics weighted by turnover and ABS sampling weights.

D Production markup estimation

Table D.1: Dynamic Panel Production Function Estimates MA(0) Assumption

	(1) OLS (full samp)	(2) OLS (MA(0) samp)	(3) A-H MA(0)	(4) B-B MA(0)
Ln(Materials)	0.905***	0.908***		0.846***
	(0.051)	(0.040)		(0.058)
Ln(Wagebill)	0.060	0.064		0.102**
	(0.054)	(0.068)		(0.034)
Ln(Fixed assets)	0.076	0.075		-0.002
	(0.046)	(0.051)		(0.031)
Delta Ln(Materials)			0.870***	
			(0.041)	
Delta Ln(Wagebill)			0.106***	
			(0.037)	
Delta Ln(Fixed assets)			-0.026	
			(0.029)	
Lagged Ln(Revenue)				0.559***
				(0.096)
Lagged Ln(Materials)				-0.488***
				(0.094)
Lagged Ln(Wagebill)				-0.043
				(0.045)
Lagged Ln(Fixed assets)				0.038
				(0.026)
N obs.	165	143	143	143
N firms	10	10	10	10
Adj. R2	0.974	0.970	0.921	
Wald p-val for CRS	0.283	0.224	0.291	
Hansen-J p-val			.	1.000
F statistic			7.12	29.21

Note: standard errors in parentheses clustered at the firm level. 'Delta' denotes 1-period differences and 'Lagged' denotes 1-period lags. */**/*** denote significance at the 10/5/1 percent level respectively.

Table D.2: Dynamic Panel Production Function Estimates MA(1) Assumption

	(1) OLS (full samp)	(2) OLS (MA(1) samp)	(3) A-H MA(1)	(4) B-B MA(1)
Ln(Materials)	0.905***	0.899***		0.863***
	(0.051)	(0.036)		(0.052)
Ln(Wagebill)	0.060	0.055		0.119**
	(0.054)	(0.067)		(0.045)
Ln(Fixed assets)	0.076	0.088		0.006
	(0.046)	(0.051)		(0.026)
Delta Ln(Materials)			0.870***	
			(0.057)	
Delta Ln(Wagebill)			0.122***	
			(0.039)	
Delta Ln(Fixed assets)			0.022	
			(0.032)	
Lagged Ln(Revenue)				0.580***
				(0.104)
Lagged Ln(Materials)				-0.517***
				(0.102)
Lagged Ln(Wagebill)				-0.069
				(0.045)
Lagged Ln(Fixed assets)				0.032
				(0.027)
N obs.	165	132	132	132
N firms	10	10	10	10
Adj. R2	0.974	0.970	0.922	
Wald p-val for CRS	0.283	0.281	0.622	
Hansen-J p-val			.	1.000
F statistic			5.52	220.54

Note: same as note to table D.1.

Table D.3: Production Function Coefficients Implied by Blundell-Bond Results

	ARMA(1,0)	ARMA(1,1)
Implied coefficients		
Ln(Materials)	0.878***	0.866***
Ln(Wagebill)	0.079***	0.080**
Ln(Fixed assets)	-0.015	0.002
Lagged Ln(Revenue)	0.648***	0.756***
Comfac	0.032	0.156

Note: same as note to table D.1.

E Demand-side markup estimation

E.1 Derivation of demand side markup formula

Assume that firms statically compete in prices under full information (Bertrand Nash competition) in each year. A firm f that produces a set of model F_f in market t with market share $s_k(p_k)$ of model $k \in K$ at price p_k, faces marginal cost c_k and pays fixed cost C_f, then maximises profits from model k Π_f with respect to price (dropping the market subscript t):

$$\max_{p_k} \Pi_f = \sum_{k \in F_f} (p_k - c_k) s_k(p_k) - C_f.$$

This yields the following set of FOCs for all $k \in K$:

$$\frac{\partial \Pi_f}{\partial p_k} = s_k(p_k) + \sum_{r \in F_f} (p_r - c_r) \frac{\partial s_r(p_r)}{\partial p_k} = 0.$$

Rearranging and stacking together FOCs across all models and firms gives (in vector/matrix notation):

$$\underset{K\times 1}{c} = \underset{K\times 1}{p} + \underset{K\times K}{\Omega(p)^{-1}} \underset{K\times 1}{s(p)}$$

where $\Omega(p)$ is a a $K \times K$ matrix with cell-entries corresponding to derivatives with respect to the market share if product j and r are produced by the same firm, i.e.

$$\Omega_{rk}(p) = \begin{cases} \frac{\partial s_r(p)}{\partial p_k} & \text{if } r, k \in F_f \\ 0 & \text{otherwise.} \end{cases}$$

Inverting gives an expression for markups defined as the Lerner index:

$$\frac{p_k - c_k}{p_k} = \frac{[-\Omega(p)^{-1} s(p)]_k}{p_k},$$

where $[-\Omega(p)^{-1} s(p)]_k$ denotes the k^{th} element of the $K \times 1$ vector $[-\Omega(p)^{-1} s(p)]$.

Alternatively, the price cost ratio is:

$$\frac{p_k}{c_k} = \frac{p_k}{p_k + [\Omega(p)^{-1} s(p)]_k}$$

Prices p_k and market shares $s_k(p)$ are observed in the data. Elements of the matrix $\Omega(p)$ are obtained from our estimates of demand parameters.

E.2 Additional demand estimation results

In addition to the nested logit model, we considered a random coefficient model following Berry et al. (1995). As discussed in the main part of the paper, this gives us largely insignificant results. We therefore base demand-side markup estimates in the main part of the paper on our nested logit model. We present the BLP-style model and results in the following.

In this appendix, we consider the following demand system. In each year t households (i) decide whether to buy a car model k or choose the outside option ($k = 0$). Households maximise their conditional indirect utility U_{ikt}:

$$U_{ikt} = \beta_{it} x_{kt} + \alpha_{it} p_{kt} + \xi_{kt} + \epsilon_{ikt},$$

where x_{kt} denotes a vector of characteristics of model k in year t, p_{kt} is the price of model k in year t, ξ_{kt} is an unobserved demand shifter, and ϵ_{ikt} is demand shock following a Type-1 extreme value distribution (i.i.d. across products). Since we observe data aggregated at the UK level, we define markets as respective years t. We define the market share of product k in market t as number of sales divided by the number of households in the UK in year t. The outside option (i.e. not buying a new car) accounts for the largest market share in all years of our sample (around 0.9).

To allow for heterogeneity across consumers in their valuation of attributes we interact draws from the UK income distribution[23] and unobserved preferences with prices and car characteristics. Individual coefficients take the following form:

$$\begin{pmatrix} \alpha_{it} \\ \beta_{it} \end{pmatrix} = \begin{pmatrix} \bar{\alpha} \\ \bar{\beta} \end{pmatrix} + \Pi D_{it} + \Sigma v_{it}, \tag{18}$$

where D_{it} is income draw of individual i in year t and values v_{it} are drawn from a standard normal distribution. We draw income from the UK Family Resources Survey (FRS) using sampling weights, and demean as well as divide values by the observed standard distribution. In practice we restrict some of the elements in Π and Σ to zero, i.e. we do not interact every characteristics with income/unobserved heterogeneity. That is, in our main specification we interact prices with income, and interact draws from the normal distribution with the constant and horsepower-to-weight ratio. The inclusion of consumer heterogeneity through draws from observed and unobserved distributions should allow for more realistic substitution patterns. Nevo (2000) outlines market share formulas and expressions for elasticities in detail. In the interest of brevity we do not show these formulas here and refer the reader to the summary in Nevo (2000).

With the vector of instruments Z_{kt} at hand we can construct the following set of moments across all models k in each market t to estimate our vector of parameters $\theta = (\alpha, \beta, \Pi, \Sigma)$:

$$\mathbb{E}\left[\xi_{kt}(s_{kt}, p_{kt}, x_{kt}; \theta) Z_{kt}\right] = 0.$$

The key identifying assumption is that the unobserved demand shock ξ_{kt} is uncorrelated with our vector of instruments Z_{kt}.

We estimate the model using the PyBLP package.[24] The main estimation technique builds on Berry et al. 1995, and the PyBLP package allows us to implement many of

23. We use data from the Family Resources Survey (FRS) to generate the income draws.
24. See Conlon and Gortmaker (2020, 2023) for more details. A detailed documentation of PyBLP can be found here: https://pyblp.readthedocs.io/en/stable/.

the best practices pointed out by more recent literature. We simulate markets consisting of 1,000 individuals, using Modified Latin Hypercube Sampling (MLHS) following Hess et al. (2006) to draw from the standard normal distribution.[25] We impose a tight convergence criterion ($1e^{-12}$), and use the L-BFGS algorithm.

Table E.1: Random coefficient model estimates

Variable	$\bar{\alpha}$, $\bar{\beta}$ (Means)	Σ (Std deviations)	π (Income interactions)
Prices	-0.108	0.001	-0.002
	(0.05)	(0.21)	(0.03)
Hp/Weight	28.958	–	–
	(15.29)	–	–
Entry/Exit	-2.204	–	–
	(0.08)	–	–
Time Trend	-0.052	–	–
	(0.03)	–	–
Recession	-0.609	–	–
	(0.19)	–	–
Constant	–	–	1.905
	–	–	(0.95)

Note: Results from our baseline random coefficients model. The first column reports estimates of linear coefficients (means). The second column shows estimated coefficients from interactions with draws from a standard normal distribution (which can be interpreted as standard deviations from the mean). The third column shows estimated coefficients from interactions with income draws. The specification includes make fixed effects and standard errors are clustered at the model level. Number of observations is 5590.

Table E.1 shows results of the full random coefficients model. The vector of characteristics from equation x_{kt} contains the horsepower-to-weight ratio, an indicator whether a model k is observed for the first or last time in our sample in year t, a time trend, and a an dummy variable for recessions. We additionally include make fixed effects to account for unobserved characteristics that are constant within a make across years (e.g. the reputation of a make). We instrument for prices using the lagged real exchange rate relative to the UK following Grieco et al. (2023).

The linear term on prices is negative and significant with a value of -0.11. We include an interaction of prices with draws from the standard normal distribution and interactions of prices and the constant with draws from the income distribution in this baseline specification. The coefficient of interactions of prices with both types of draws are insignificant. The interaction of the constant with income is just significant at the 10%-level. The positive coefficient implies that consumers with higher income generally have a higher valuation of the outside option.

Trends in markups resulting from the full random coefficient model look very similar to those of the nested logit model.

25. Using quasi-random sampling techniques like MLHS or Halton draws tends to improve precision of estimates. See Train (2009) for detailed explanations and simulations.

F Supplementary results

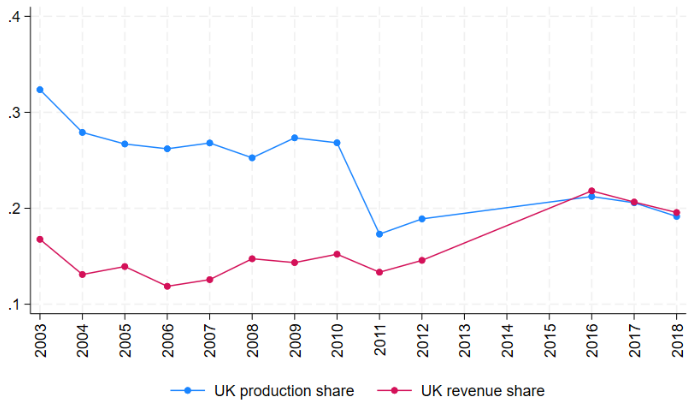
Table F.1: Demand Nest Summmary Statistics

	(1) Nest 1 mean/sd	(2) Nest 2 mean/sd	(3) Nest 3 mean/sd	(4) Nest 4 mean/sd
Kerbside weight kg (average across trims)	1170.9	1593.3	1820.3	2101.8
	(178.3)	(193.4)	(257.3)	(268.0)
HP (average across trims)	101.9	158.3	413.7	252.2
	(26.4)	(41.4)	(114.2)	(78.5)
Price ('000£)	17.3	30.3	93.6	54.6
	(5.5)	(8.0)	(56.5)	(17.4)
Observations	2562	2545	252	750

Note: table shows means (and standard deviations in parentheses) of weight, horsepower (HP), and prices by nest. We generate nests using four nests using a k-clustering algorithm based on weight and horsepower.

For 2003-2012 and 2016-2018 we can use SMMT data on production and exports to compare our estimates of UK revenue shares with UK production shares. This comparison suggests our UK revenue share estimates are plausible, although the two are less comparable in earlier years, which could be due to differences in the SMMT methodology prior to 2016.

Figure F.1: UK revenue and production shares over time



Note: figure shows mean UK revenue and production shares. The former is calculated by inferring UK revenue from JATO data and taking total revenue from HO. The latter is calculated by comparing SMMT export and production data.

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