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Evaluating merger effects

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Abstract
This paper proposes a new algorithm with which to identify the potential effect of mergers by comparing the outcomes of interest in areas of overlap for the merging parties vis-à-vis areas of no overlap within a difference-in-differences estimation framework. Utilizing our proposed algorithm enables researchers and policymakers to perform retrospective merger evaluation studies that look at the effects of mergers on both price and non-price aspects. We demonstrate the applicability and value of our proposed methodology by examining the effects on price and product variety of four mergers of the late 1980s and the 1990s on the U.K. car market.

Keywords: mergers, *ex post* policy evaluation, automobile industry
JEL codes: L0; L1; L4; L5

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1 Introduction

There is growing interest in retrospective merger studies among competition authorities on both sides of the Atlantic, which stems from the need to better understand both the short- and long-term impacts of those mergers on consumer welfare, but also as a way to evaluate and improve the effectiveness of their decision-making (Ormosi, et al., 2015; Carlton, 2022). At the same time, there is an important academic debate (Angrist and Pischke, 2010; Nevo and Whinston, 2010) that points to the need for more *ex post* studies to evaluate the simulation tools used to analyze such mergers *ex ante*. Despite the significant private and public resources spent on predicting the effects of horizontal mergers, there is relatively little *ex post* empirical evidence of their effects to guide regulators. Furthermore, there is considerable recent research on the broader effects of merger activity (Amin and Boamah, 2021; Chiu, et al., 2021).

Moreover, the vast majority of existing retrospective studies focus predominantly on the price effect of mergers, treating product characteristics as exogenous and fixed over time (the literature is discussed below). Although innovation and product development take time, the cessation or repositioning of existing products can also represent an important strategic decision that affects consumer welfare yet can be implemented much more quickly. Indeed, the fact that mergers can affect the available product portfolio has been highlighted in recent research (Draganska et al., 2009; Sweeting, 2010; Mazzeo et al., 2018; Fan, 2013; Wollman, 2018; Fan and Yang, 2020). However, owing to the lack of a broadly implementable empirical framework with which to examine firms' post-merger product-portfolio decisions, the available *ex post* evidence regarding the effects of such decisions is scant (Berry and Waldfogel 2001; Sweeting, 2010; Ashenfelter, Hosken, and Weinberg, 2013; Argentesi et al., 2018).

In this paper we propose a new methodology to perform merger evaluation *ex post*, in which we use the product characteristics space to define treatment and control groups. The view of products as bundles of characteristics (Lancaster, 1971) has become the benchmark model in industrial organization owing to the innovations in discrete choice models during the last few decades (Berry, 1994; Berry et al., 1995). We identify the degree of product overlap between merging firms by using the proximity of their products in the characteristics space. The fundamental idea of our treatment and control assignments is that the competitive effects of a merger are expected to be strongest in the areas where there is most closeness and/or overlap of characteristics between the merging parties' products. The simple intuition is that in areas where merging firms overlap there will be a more pronounced change in competitive conditions because there will, by definition, be a decrease in the number of firms competing. Therefore, we should be able to identify the potential effect of mergers by comparing the prices or the product variety of the merging parties in areas of overlap (the treatment group) vis-à-vis areas of no overlap (the control group) within a standard difference-in-differences (DiD) estimation framework.

We demonstrate the applicability of our proposed methodology by examining four mergers realized in the U.K. car market in the late 1980s and the 1990s. These mergers had different strategic motivations and were all cleared from a competition perspective by the European Commission at the time, so we do not expect to find any serious competitive threats. We use these merger cases to highlight the usefulness of our proposed algorithm by comparing it with a simpler approach that utilizes common car segments as the treatment market of the merging firms. We show that there are significant differences between the two approaches that can often lead not just to different levels of statistical significance, but to results of opposite signs.

Our paper both relates to and contributes to several strands in the literature. First, it contributes to the growing literature on retrospective merger evaluation using both pre- and post-merger data (see Borenstein (1990) and Kim and Singal (1993) on airline mergers, Panetta and Focarelli (2003) on banking, McCabe (2002) on journal publishers, Ashenfelter and Hosken (2010) and Ashenfelter et al. (2015) on food and non-food grocery sectors, Ashenfelter et al. (2013) on the home appliance sector, Hastings (2004) and Taylor and Hosken (2007) on retail gasoline, Connor, Feldman, and Dowd (1998) and Dafny (2009) on hospitals, Björnerstedt and Verboven (2016) on pharmaceuticals, Allain et al. (2017) and Argentesi et al. (2018) on supermarkets, and Aguzzoni et al. (2016) on the retail market for books). Our work draws specifically upon the literature that uses geographic variation in markets to define areas in which the two merging parties overlap versus areas where they do not. However, rather than use geographic differentiation, which is a critical element in defining the relevant market in some industries, we exploit differentiation in product characteristics because this covers the vast majority of industries and can be applied much more widely.

Second, our work also relates to the small but growing literature that studies the impact of mergers on decisions taken by firms that do not concern price. For example, several papers analyze the effects of the merger wave that took place in the U.S. radio industry at the end of the 1990s: Berry and Waldfogel (2001) find that these mergers increased variety and Jeziorski (2014) quantifies the effect of this increased variety on both sides of the market (i.e., listeners and advertisers); Sweeting (2010) reports that these mergers did not affect aggregate variety, because changes affecting the merging parties and their competitors offset one another.

The evidence for the impact of mergers on the acquirers' innovation performance in terms of proxies for inputs to the R&D process report a neutral effect (Danzon et al., 2007; Hall, 1988, 1999; Healy et al., 1992) or a negative one (Hall, 1990; Hitt et al., 1991, 1996; Ornaghi, 2009; Ravenscraft and Scherer, 1987). Similarly, studies looking at the effect of acquisition on proxies for the acquirers' R&D output also report a neutral effect (Prabhu et al., 2005) or a negative one (Hitt et al., 1991; Ornaghi, 2009). Finally, studies from retail markets have found a substantial reduction in variety on the part of the merging parties in the case of home appliance manufacturers (Ashenfelter, Hosken, and Weinberg, 2013), and a significant reduction in product variety and a move toward a smaller and more expensive assortment in the case of supermarket mergers (Argentesi et al., 2018).

The remainder of this paper is organized as follows: Section 2 discusses the estimation and identification of merger effects and introduces our proposed algorithm, and Section 3 presents its application to the measurement of effects of historical mergers in the U.K. car industry. Section 4 describes our estimation framework, with the results for effects on both price and variety being presented in Section 5. We draw brief conclusions from our paper in Section 6.

2 Estimation and Identification of Merger Effects

The retrospective merger evaluation literature has used two modeling approaches to analyze counterfactual merger activity scenarios. The first approach aims to directly estimate the price effect by comparing average prices before and after the merger, effectively holding input costs and seasonal factors constant. This approach is implemented by estimating a specification of the following type for each product i and time period t:

$$y_{it} = \alpha_i + \beta_i PostMerger_t + \gamma_i Cost_t + \delta_i Demand_t + \varepsilon_{it} \tag{1}$$

where y_{it} is the outcome of interest (typically the effect on prices, but also other outcomes such as the effects on investment or product variety), α_i is product fixed effects, $Cost_t$ can be a vector of various measures of raw material costs, and $Demand_t$ is a vector capturing factors that may affect demand, such as advertising or the prices of substitutes/complements. The parameter of interest here is β_i, which measures the increase in product i's outcome of interest after the merger. The identification assumption is that the *Cost* and *Demand* input parameters capture everything that could materially change the outcome of interest other than the merger (for examples from the literature, see Peters, 2006; Weinberg and Hosken, 2013). Empirically, it is often challenging to find information on the demand and input costs that vary with the same frequency as the price data, especially at the product level when it comes to differentiated markets. In theoretical terms too, this approach has been challenged because it is hard to argue convincingly that all unobserved factors that might affect price (or other outcomes) post-merger, other than market power, have been captured.

The second modeling approach, which tries more explicitly to control for any other confounding factors that may also have changed at the time of the merger, is the DiD methodology, which is now the technique most commonly used in the literature to address this task. The DiD methodology entails a comparison of two properly identified groups: a treated group that is affected by the "treatment" (e.g., the merger), and a control group that is not affected by the treatment. The two groups are compared before the treatment and after the treatment (i.e., pre- and post-merger). A general specification of the DiD methodology in this instance would be:

$$y_{it} = \alpha_i + \beta_i (Treat_i \times PostMerger_t) + \gamma X_i + \tau_t + \varepsilon_{it} \tag{2}$$

where $Treat_i$ is a binary indicator that serves to identify the treatment group, X_i is a vector of control variables that may include product characteristics as well as various product or other (brand, segment, etc.) fixed effects, and τ_t is time fixed effects.

The strength of this method is that it isolates the effect of the merger from any other factors that (i) may affect the trend in the outcome of interest, and (ii) may be related to the differences between the treatment and control groups. A critical aspect of implementing the DiD approach is proper definition of these two groups. In its simplest form, making the assumption that the merger does not have an impact on competitors' prices, the treatment group will consist of the products of the merging parties, and the control group will be all of the other competing products within the relevant market (for example, see Björnerstedt and Verboven, 2016). However, where strategic complements are involved, or there is some degree of coordination, the merger may also affect competitors' prices. In this case, the coefficient β_i that captures the difference in price between the merging and the competing products can be viewed as a lower bound of the "true" effect of the merger on price.

Mergers, however, are do not emerge randomly. The merging firms are likely to be different from non-merging firms in unobserved ways that can affect the outcomes of interest. This introduces a fundamental selection problem that may bias estimates of the impact of a merger. One possible solution to this problem, introduced by Eckbo (1983), is to discard the merging firms from the analysis and instead focus on the responses of their rivals to the merger. Here, the key idea is that if the merging firms exercise their market power by raising prices, *ceteris paribus* we would expect their close competitors to raise their prices as well (strategic complementarity). Hence, this rival analysis compares the prices of rivals that are competing with the merging parties to the prices of those not under the influence of the merging parties.

One of the first implementations of this idea, taking advantage of geographic variation in retail markets, was conducted by Hastings (2004). Hastings studied the retail gasoline market and wanted to measure the price effect of a merger between two firms in the greater Los Angeles and San Diego metropolitan areas. Because of the wide geographical dispersion of gas stations and the local nature of competition, Hastings conducted a rival analysis, defining the treatment group as gas stations that were competing locally with the stations of the merging parties, and the control group as gas stations that were not in the vicinity of those of the merging parties. In other words, geographic dispersion was considered to be a pre-determined choice variable that could not be easily changed within a short period of time, thereby allowing the researcher to separate "close" and non-close competitors that would be differentially affected by the merger. This idea has since been widely implemented across different retail markets and countries to consider both price and non-price effects of mergers (Allain et al., 2017; Argentesi et al., 2018; Aguzzoni et al., 2016).

Unfortunately, many product markets lack this geographic differentiation dimension, undermining its general applicability. Thus, rather than adopting a geographically based identification strategy, we draw upon a substantive literature and instead look to exploit changes in the product characteristics space. The view of products as bundles of characteristics (Lancaster, 1971) has become the benchmark model in industrial organization owing to the innovations in discrete choice models of Berry (1994) and Berry, Levinsohn, and Pakes (1995). Product characteristics can be used both to describe the mean utility across heterogeneous consumers, and to guide substitution patterns, in the sense that products with similar characteristics will be closer substitutes.[5] In a similar spirit, we utilize the idea of "how close products are" with reference to the products' characteristics to operationalize areas in which the merging firms overlap and those in which they do not.

Our treatment and control assignments draw on the intuitive notion that the competitive effects of a merger will be stronger in the areas of characteristics where there is an overlap between the merging parties (i.e., where products are close together in the characteristics space) than in areas where the parties produce products that do not exhibit such overlap. The simple intuition is that in areas where the merging firms overlap there will be a stronger change in competitive conditions because there will be a decrease in the number of competing firms. Therefore, we can identify the potential effect of a merger by comparing the prices and variety of the merging parties in areas of overlap (the treated group) in relation to those in areas of no overlap (the control group).

2.1 Proposed algorithm

Our algorithm uses the characteristics spaces of products to define overlapping and non-overlapping areas. To understand the algorithm's underpinning intuition, we present the procedure below, using the assumption that the products differ in only two dimensions.

The algorithm works as follows: take a product from one merging party at time T-1 (one period before the merger) and draw a circle of radius R around it. This identifies its relevant market of

[5] See also the work of Gans and Hill (1997) on measing product diversity in an industry.

close competitors. If this market includes (or intersects with) the equivalent relevant market of at least one product of the other merging party, then it is an overlapping market and we will designate it as the treated market. However, if the relevant market of the first party's product does not include or intersect with that of any product of the other party, then this is a non-overlapping market and we designate it as the control group. Last, we identify the products of any competitors that fall within either the treatment or the control areas so designated. We then hold these overlapping and non-overlapping areas constant after the merger and we study the evolution of the outcome of interest.

Graphically, assume two merging firms (M1 and M2), each of which has two products. As shown in Figure 1, both of M1's products intersect with one of M2's products, creating the blue overlapping market, whereas M2's second product has a non-overlapping relevant market (in red). Products from the various other competitors (indicated as Cs in the figure) are then categorized according to whether they fall into the overlapping or non-overlapping markets, or discarded if they do neither.[6]

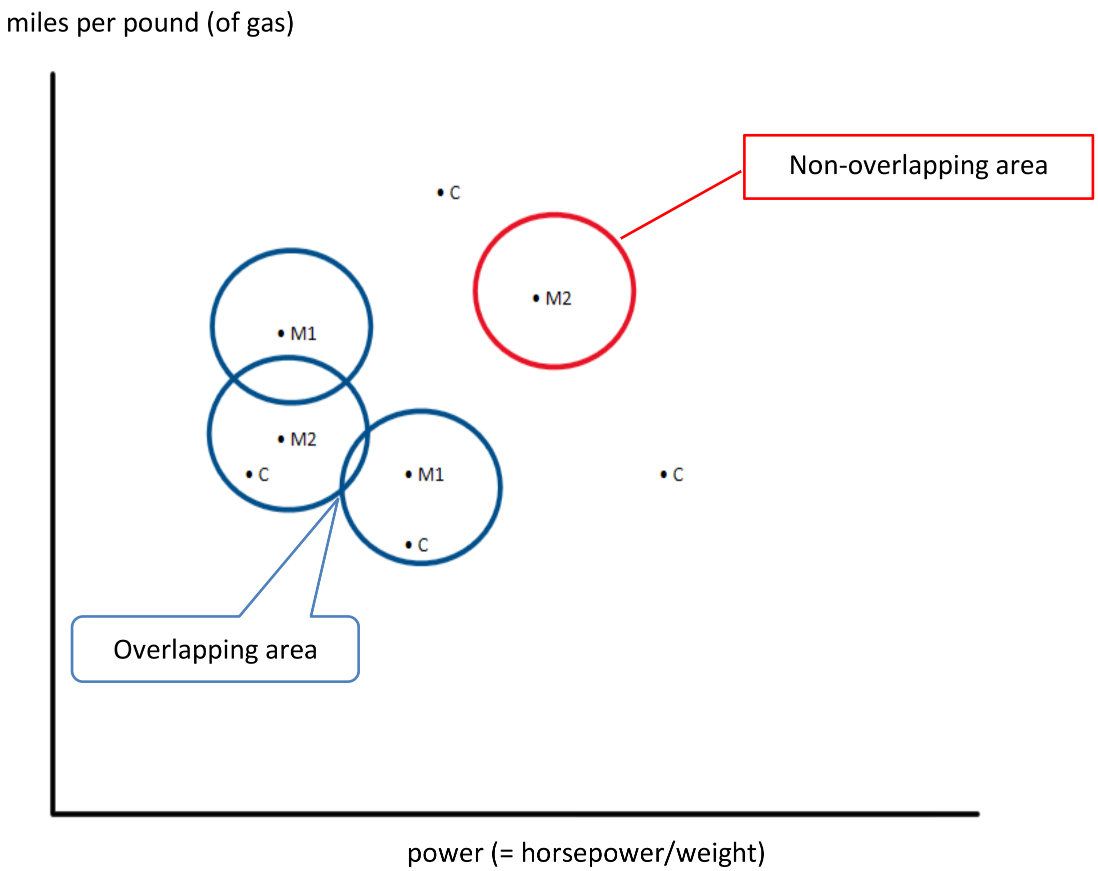
The theoretical rationale behind this algorithm is that choices relating to key characteristics are long-term decisions and cannot easily be changed, hence they can be used to define who the close competitors are (i.e. the ones most likely to be affected) at the time of the merger. This argument is analogous to that associated with the location decisions made by firms in the literature that defines geographic markets, as previously discussed (e.g., Hastings, 2004; Argentesi et al., 2018).

Relying on key product characteristics to designate overlapping markets also means that we do not have to rely on subjective market segmentations. For example, the car market is typically segmented along size lines, such as "mini," "small," or "medium." But, of course, a larger model in the "small" category may be a closer competitor for a smaller "medium" car than other "medium" cars sold in the market. More specifically, in 1995, while both the Fiat Punto and SEAT Ibiza car models belonged to the same mini/super-mini segment, the former had a version that was closer than the latter to a version of the Ford Escort, which belonged to the small family segment. In other words, *a priori* segmentation of products creates artificial boundaries that can be

[6] For example, the two C products in Figure 1 that do not fall into either the blue or the red circles are discarded.

misleading. Measuring the closeness of competitors solely on the basis of their key characteristics resolves this issue and better reflects the underlying patterns of substitutability.

FIGURE 1 – EXAMPLE OF OVERLAPPING AND NON-OVERLAPPING AREAS



Notes: The figure provides an example of overlapping and non-overlapping areas for the two merging firms (M1 and M2, where each has two products) and their various competitors (indicated as C) in the two-dimensional characteristics space of miles per pound and power. The blue and red circles are drawn for a given radius *R* around the merging products.

This procedure provides us with a treatment group that, in principle, contains products from both of the merging firms (M1 and M2), together with some from their competitors (C). At the same time, the control group also consists of products from one or both of the merging firms, as well as possibly some from competitors. This allows researchers to undertake various DiD comparisons, depending on data availability and the policy question of interest. For example, one such could involve all of the treated products being compared to all of the products in the control group. Alternatively, one could focus separately on the acquiring firm or the acquired firm to examine any differential behavior post-merger. Last, but not least, one could use Eckbo's (1983) approach and concentrate the analysis only on the rival firms within the treatment and control groups.

In practice, of course, most products have more than two important characteristics, so it is important to allow for the "distance" between any two products to be multidimensional. We implement this algorithm by calculating the Euclidean distance between any two products x and y with N characteristics:

$$d(x, y) = \|x - y\| = \sqrt{\sum_{i=1}^{N} (x_i - y_i)^2}$$

In order to define which products are close, we use a threshold, G. Let x be the product of one of the merging parties and y that of the other. If the distance between them is less than or equal to G, then the space around the two products would represent an overlapping area; otherwise, the spaces around them would be non-overlapping areas.

To define these areas, we would use the same threshold, G. In a two-dimensional scenario, (i.e., two product characteristics), these areas are, graphically, circles of radius G around the products; in a three-dimensional scenario, these areas would be spherical. In other words, if x and y are "close" and the distance of another product z from at least one of them is less than or equal to G (i.e., $d(z, x) \leq G$ or $d(z, y) \leq G$), then it would belong to the overlapping area. However, if x and y are not "close" (i.e., $d(x, y) > G$), then z would belong to a non-overlapping area. Products that belong to the overlapping areas would be the treated products, while those in the non-overlapping areas would form the control group.

How does our proposed approach fit within the existing literature? The standard approach to market definition is the application of the 'small but significant and non-transitory increase in price' (SSNIP) test. Based on this test, the relevant market is the smallest group of products for which a hypothetical monopolist could profitably impose a small, nontransitory but significant increase in price. Since the profitability of a price increase depends on the extent of product substitutability, application of this test relies on first estimating a demand model for all products. Therefore, a potential algorithm for retrospective merger evaluation studies using this approach would be as follows: (1) estimate a demand model and calculate elasticities, (2) apply the SSNIP test and define market boundaries, (3) define products of the merging parties (together with competitors' products) that belong to the same sub-market as the treated market and products of the merging parties (and competitors' products) that do not belong to the same sub-market as the control market and apply the DiD methodology.

The obvious appeal of structural approaches is that market delineation is based on a framework where consumers maximize their utility and firms maximize their profits (at least in static Nash-Bertrand sense). However, such an approach would also have several significant limitations. First, computational complexity is considerably higher than the approach we propose, as one needs to estimate an appropriate demand model before the merger while making a number of important analytical choices. For example, the researcher needs to decide whether to model demand is a static or dynamic system, which instruments to use, and which estimation methodology to employ (e.g. an almost ideal multilevel demand system à la Hausman, 1996, or a distance metric system à la Pinkse and Slade, 2002, or, some of the variants of random utility model such as nested logit, random coefficients logit, etc.). Second, is extremely difficult to accommodate product entry and exit using standard approaches. Our algorithm relies on identifying overlapping or non-overlapping areas that stay the same after the merger allowing for product entry and exit to be incorporated into the analysis (as well as for minor alterations of the products' characteristics). In contrast, structural methodologies focus on specific products' elasticities before the merger and hence any product change imply that a new market definition exercise needs to be performed again after the merger. Perhaps due to the computational complexity, there is no empirical study, that we are aware of, that has performed such a retrospective merger evaluation analysis.

We see our proposed methodology to be complementary to the more computationally intensive approach of market definition utilizing structural model estimation. The key advantages of following our proposed algorithm to define overlapping and non-overlapping areas are: first, that it relies on the products' characteristics and not on a pre-determined or arbitrary categorization of products. Second, the fact that we can hold these characteristics areas fixed after the merger means that we can credibly analyze not only the merger's effect on the prices of existing products, but also on product variety, because we can also observe product entry and exit post-merger. Third, the algorithm we propose is less complex and computationally demanding, so it can be readily implemented, and it is also transparent and flexible. The algorithm can also be applied in a variety of markets where consumers have heterogeneous preferences over products' characteristics. In the next section, we demonstrate its applicability by considering merger activity in the U.K. car market.

3 Application: Mergers in the U.K. Car Market

We use the U.K. car market and a number of selected mergers to demonstrate the usefulness of our framework. The car industry is one of the most heavily studied markets in the literature (Berry et al., 1995; Verboven, 1996; Petrin, 2002; Wollmann, 2018) and several studies have shown that in estimating the demand for cars, while they may be differentiated along multiple dimensions, only a few characteristics really matter when looking at the market overall (e.g. Berry et al., 2004).

We select the U.K. car market because it is one of the largest and most competitive markets within Europe. However, the mergers we evaluate here were global in nature and the local U.K. market was not their principal concern. Hence, we can reasonably assume that the merger decisions were exogenous to evolution and competition within the U.K. market.

3.1 Data

The data set consists of a complete set of unit sales, price and product attribute data for all automobile models and their variants sold in the U.K. automobile market between 1983 and 1999. Annual sales were obtained from the Society of Motor Manufacturers and Traders. Listed prices were taken from *Parkers' Guide to New and Used Prices* and the *Motorists' Guide to New and Used Car Prices,* with Augur-Tech Ltd providing access to its database of car attributes.[7] Contemporaneous trade publications and the official allocations of the U.K. government's

[7] Augur-Tech Ltd was an internet design consultancy for the motor industry whose data was provided directly by all automobile manufacturers operating in the UK. Attributes recorded by Augur-Tech were also recorded in the major trade publications. We thank Augur-Tech for allowing us access to this data.

Department of Trade and Industry (DTI) are used to define the segment classifications. This segment structure was also that used by manufacturers in the U.K. and consisted of eight market segments: mini/supermini, small, medium, executive, luxury, sports, 4×4, and personal carrier. Summary statistics of the key automobile characteristics for the market overall and per market segment are provided in Table 1.

[Insert Table 1]

An important novelty of the dataset is that we capture the multiple variants of models active in the market, which are, ultimately, the products marketed. The automobile industry comprises multi-product firms that often market their products through different “brands” and multiple “models” that are themselves differentiated and sold in “variants.” These variants differ, often substantively, in their product characteristics and prices. A well-known example of differentiation in the automobile market is the Volkswagen Golf, which is marketed in the form of multiple products, ranging from a relatively affordable baseline L version to the iconic high-performance GTi, which sells for roughly twice the price of the baseline product. The Golf belongs to Volkswagen A.G. (VAG), which markets products under four distinct brands – Skoda, SEAT, Volkswagen, and Audi. Having information on price and non-price effects enables us to examine both within the same context. Summary statistics of the number of car models for the market overall and for each market segment are provided in Table 2.

[Insert Table 2]

3.2 The mergers

During the 1980s and 1990s there were many changes in the ownership structure of the automobile industry. In this paper we examine the mergers of SEAT with the Volkswagen group in 1986, of Jaguar with Ford in 1990, of Rover with BMW in 1994, and of Mazda with Ford in 1996. While important, none of these mergers raised serious competition concerns. Hence, the European Commission decided not to oppose the notified operations, and declared them compatible with the European Common Market and with the functioning of the European Economic Area (EEA) Agreement.[8]

SEAT–VAG. In 1982, VAG initiated cooperation with the Spanish automobile producer SEAT S.A. in relation to the production of Volkswagen's Passat and Polo models. The motivation for this cooperation was that VAG's management wanted access to Spanish production plants to improve efficiency and reduce total production costs. This cooperation continued until June 1986, when VAG acquired 51% of SEAT's shares, thereby becoming the majority shareholder of the Spanish firm, and increased its interest to 75% by the year's end (Laux, 1992, p. 232). The reported motive for the final acquisition of SEAT, in addition to increased economic efficiency, was that VAG wanted to gain further access to the southern European automobile markets, and to incorporate another brand into the firm's portfolio of automobiles (Rudholm, 2006). Before the acquisition, both parties were producing cars in the mini/super-mini segments, while the VAG group was also producing cars in the small family, medium, executive, and sports segments of the market.

Jaguar–Ford. In 1989, the Ford Motor Company announced that it planned to buy Jaguar Plc for a total cost of nearly $2.38 billion.[9] The deal was completed in 1990 and reflected the continuing consolidation of the world's auto industry and the eagerness of big carmakers to acquire prestigious brands. However, Ford had very little idea of the problems that Jaguar was facing (Gomes et al., 2007). The increased competition from the Japanese move into the luxury-car sector, the high cost of developing new models, and a downturn in the crucial American market had made it increasingly difficult for smaller carmakers like Jaguar to go it alone. To observers, Ford's offer, for a company that made 51,939 cars in the year prior to the purchase and was barely breaking even, seemed extraordinarily high. But Ford executives made it clear that they were paying a premium for the Jaguar name and would invest heavily to turn the British company into a larger-scale producer. Before the acquisition, both parties were producing cars in the sports and luxury segments. In addition, Ford was also producing cars in the mini/super-mini, small family, medium, and executive segments.

[8] This decision was adopted in the application of Article 6(1)(b) of Council Regulation No. 4064/89.

[9] Ford to Buy Jaguar for $2.38 Billion. http://www.nytimes.com/1989/11/03/business/ford-to-buy-jaguar-for-2.38-billion.html

Rover–BMW. In January 1994, British Aerospace announced the sale of its 80% majority share of the Rover Group to BMW, which paid the equivalent of $1.35 billion, and nearly doubled that figure in subsequent investment. At the time, BMW's reported aim was to achieve greater economies of scale, which – with Rover's production capacity of 700,000 cars, compared to BMW's capacity of only 500,000 – a merger facilitated (Walters, 2000). However, contemporaries pointed out that there were other substantial advantages beyond scale effects to BMW in that Rover also maintained the technological leader in 4x4 production, Land Rover (Gould, 1998), and provided the opportunity to develop and popularize the iconic Mini. So, while before the acquisition both parties were producing cars in the medium, executive, and sports segments, only BMW was producing cars in the luxury segment, while only Rover was producing cars in the mini/super-mini, small family, and 4×4 segments.

Mazda–Ford. In 1979, Ford acquired a 24.5% shareholding in Mazda, with the two companies maintaining their autonomies (Rubenstein, 1992). Japanese car manufacturers had managed to improve productivity and quality in the small car market far beyond what most North American firms had ever achieved (Cusumano, 1985). Instead of competing head on with the Japanese, Ford preferred to acquire Mazda in order to learn and be able to compete in these market segments. In 1996, Ford completed its merger with Mazda, increasing its shareholding to a 33.4% controlling stake in Mazda.[10] The partnership saw a great dissemination of know-how, and new models arose after the merger. Before the acquisition, both parties were producing cars in the mini/super-mini, small family, medium, executive, and sports segments, while Ford was also producing in the luxury, 4×4, and personal carrier segments.

4 Econometric Specification

To compare changes in products located in overlapping areas with changes in products in non-overlapping areas before and after a merger, we use the following DiD specification:

$$ln(y_{it}) = \alpha + \beta(post_t \times overlap_i) + \gamma X_i + \tau_t + \varepsilon_{it} \qquad (3)$$

[10] REGULATION (EEC) No 4064/89 MERGER PROCEDURE, Case No IV/M.741 - Ford / Mazda, Article 6(1)(b) NON-OPPOSITION Date: 24/05/1996, http://ec.europa.eu/competition/mergers/cases/decisions/m741_en.pdf

where y_{it} is the outcome of interest and, in our case, is either the price for product i in year t or the number of models produced by each brand i in year t; $overlap_i$ is a binary indicator that takes a value of 1 if the product is located in an overlapping area; $post_t$ is a binary indicator that takes a value of 1 after the merger; X_i is a vector of control variables (for the price regressions, this includes brand and segment fixed effects, country of manufacture, power (= horsepower/weight), size (= length × width), miles per pound (of gasoline), and indicators for diesel, turbo, and fuel injection system; for the variety regressions, it includes brand fixed effects only); τ_t is a full set of year fixed effects. The error term ε_{it} is assumed to be heteroskedastic and autocorrelated at the brand level.[11]

To distinguish the areas of overlap, we calculate the Euclidean distance, combining the engine capacity, power, and size of the cars. These are the same variables as those used to define varieties of each model. With three variables and a radius *R*, instead of the circles of the example in Section 2.1, we now have spheres around each car. If the spheres of two cars intersect, then these two cars are considered as close substitutes and we proceed as in the example (Section 2.1) to identify the treatment and control groups. For each merger we have used a different radius *R*. The selected *R* was determined such that we have equal sizes of treatment and control groups in the year before the merger.[12] After the merger, the sizes of these two groups can vary in either direction, that is, the result of entry and exit on the sizes of the treatment and control groups is not known, *ex ante*, from the radius *R*. A larger value of *R* may result in higher levels of entry by close competitors into either or both of the two groups.

We run our analysis for the full sample to measure the aggregate effect for both the two merging firms and their competitors, and we also explore the heterogeneity by looking at the effect separately for each of the two merging parties and their competitors. The estimation on the full

[11] We clustered the standard errors at the brand level because many of their important characteristics are likely to be correlated. For instance, car engines are not only produced on the same production lines but different engine models are used in more than one car model of the brand. Hence, there would be some correlation between these cars and, as a result, shocks associated with the production costs of a particular car engine will affect all of these models in a similar way.

[12] We selected the value for radius R so that the control and treatment groups are of equal size to emulate a random allocation of treatment as if this was a Randomized Control Trial study. To test the robustness of our findings we are also experimented with the size of the radius (+10% and -10% of its benchmark value). As we discuss later, altering the size of the radius did not fundamentally alter the findings.

sample aims to measure the overall effect of the merger at the market level, which is possibly the most relevant result for the competition authorities and consumers. The estimations on the subsamples (the acquirer, the acquired, and competitors) aim to identify the strategic reactions of the different players in the market, which helps us study the mechanism(s) driving the average effects and better explain the post-merger competitive dynamics.

A final significant decision when it comes to evaluation of the impact of the mergers concerns the size of the time window to be considered before and after the event. This will depend on data availability and the nature of the product in question in terms of its technology of production (i.e., the time to design, produce and market new products). Following the literature, we assume that firms can alter prices faster than they can alter or introduce new products. This is certainly the case in the car industry where sunk costs are known to be substantial in terms of both time and cost (Clark and Fujimoto, 1991). Hence, for prices, our benchmark window spans one year before and one year after the merger. As a robustness test, we also estimate the model allowing for a three-year lag after the merger. For product variety, our benchmark window allows three years after the merger, and we use a five-year lag to test robustness. In all specifications, we omit the year in which the merger occurred.

5 Empirical Results

We discuss the results for the four mergers below, first using price as the dependent variable in Equation (3), and second using the number of products. To highlight the value of our proposed algorithm we compare it with a simpler approach that identifies the common segments as the treatment market for the merging companies. For example, if in the SEAT–Volkswagen merger both companies were producing cars in the mini segment of the market, then this segment would be considered the treatment group. The segments in which only one or other of them was producing cars (small, medium, executive, and sports) would be designated as the control group, and any segment in which neither had any models would be excluded.

5.1 The effect of mergers on prices

Table 3 presents the results for the effects of merger on price for each of the four mergers, in chronological order. In Panel A, we use *a priori* market segments to assign products into control and treatment categories, whereas in Panel B we use our proposed algorithm, based on key product characteristics.[13] Column 1 of each panel shows the overall result of comparing overlapping and non-overlapping product areas, while we decompose this overall result in columns 2 and 3 for each of the merging parties (column 2 for the acquirer, column 3 for the acquired), and in column 4 for the competitors.

[Insert Table 3]

Looking at column 1 for both panels, we can see that none of the mergers had any significant effect on market prices, which suggests that the European Commission's assessment at the time that these mergers did not raise any serious competition concerns was justified and is consistent with expectations. However, the decomposition of the overall result reveals some important differences between the two panels.

First, as shown in column 2 of Panel A, we have not been able to estimate the coefficients for the acquiring party for the first two mergers. This is because there was very little segment overlap between the merging parties in these two cases, and also because some products exited the market post-merger. By contrast, in Panel B, where we define overlap areas according to characteristics, we are in a position to identify the price effect of these two mergers on both the acquiring and the acquired firms. As we can see in Panel B, the effect was positive and significant in the case of the Ford–Jaguar merger, something that is not identified at all in Panel A.

There are also important differences for the other two mergers: in the case of BMW–Rover, in Panel A we can see that none of the results is statistically significant, but Panel B shows a significantly negative effect for Rover and a positive effect on the rest of the competitors (at the 10% significance level). This highlights the "defensive" nature of this merger, which was aimed

[13] Tables A1 and A2 in the Appendix report the full estimation results.

at economies of scale and reorganization of production rather than the short-term acquisition of market power.

In the case of the Ford–Mazda merger, the results in Panel A reveal that there was a positive price effect for Ford, but not for any other party. However, Panel B demonstrates that the merger generated a positive effect for both merging parties, although these were too small to have an effect in aggregate on the wider market.

Again, on aggregate, given the nature of these mergers, we did not expect to find any significant price effects. However, what we want to highlight is that because our proposed algorithm relies on key product characteristics, and not on a subjective segmentation, it is more flexible and allows us to capture the competitive dynamics resulting from these mergers with greater accuracy. To gauge the robustness of our results we also varied the proposed radius +10% (Table A5, Panel A) and -10% (Table A5, Panel B) compared to our benchmark case. None of the results seem to change in any fundamental way.

5.2 The effect of mergers on variety

We measure product variety as the number of models per brand (e.g., Vauxhall) per year. However, in practice we face the issue that there are multiple versions of the same model with a variety of primary characteristics (e.g., power, size, engine capacity) but many secondary ones too (such as new climate control, audio, or safety features). For instance, the 1995 Volkswagen Golf Sport version had a 175 brake horsepower (BHP) engine and was almost twice the price of the 60-BHP base Golf model. Clearly, these two models represented two very different value propositions for potential buyers. Hence, to define different varieties, we use a combination of key car components that are both important for consumers and difficult to change (in the sense that they require significant investment by the firm). Cars with the same model name, engine capacity (measured in cubic inches), power (measured as the ratio of horsepower to weight), and size (measured as the product of length and width) are considered as being the same variety. If any of these key characteristics are different, then we consider the car to be a new model. Changes to or additions of secondary auxiliary characteristics are not considered to constitute fundamentally different cars and are counted as the same model.

With this definition in mind, Panel A of Table 4 shows the effects of the mergers on the number of products when we use market segmentation to assign to treatment and control groups, whereas Panel B utilizes our proposed algorithm, based on key product characteristics, to make these assignments.[14] Again, column 1 shows the overall result of comparing overlapping and non-overlapping product areas, while we decompose this overall result in columns 2 and 3 for each of the merging parties (column 2 for the acquirer, column 3 for the acquired), and in column 4 for the competitors.

[Insert Table 4]

Looking at column 1 throughout both panels, we can see that none of the mergers had any significant effect on product variety. However, the decomposition of the overall result in the following columns reveals some important differences between the two panels. In the SEAT–VAG merger, the segment classification in Panel A seems to indicate that VAG significantly reduced its number of models post-merger, whereas SEAT significantly increased its model count. The results from Panel B seem to concur on the increase in SEAT models, but not on the decrease at VAG. Using the better matching algorithm allows us to formulate a better control group that captures the competitive dynamics of the two merging parties more precisely. In the case of the Ford–Jaguar merger, the results from the two panels indicate agreement that there was no significant effect in terms of the number of models in the market for either the merging parties or the competitors.

The results for the BMW–Rover merger are also quite interesting. In Panel A we see that both the acquiring and the acquired firm significantly increase their model counts in the market post-merger, but in Panel B we see the opposite trend. Again, the better-matched sample is revealing different market dynamics to those of the naïve market segmentation, particularly in this merger where both firms were present in segments, such as sports or executive, in which there is wide differentiation.

The Ford–Mazda merger also reveals important differences between the two approaches. Recall that Ford and Mazda overlap in five (out of the eight) segments. In Panel A, we see no significant

[14] Tables A3 and A4 in the Appendix report the full estimation results.

effect in terms of the number of models in the market. By contrast, in Panel B, both parties are shown to significantly reduce their product portfolio post-merger, which is consistent with the observation that there was significant overlap between the two merging parties. We also test the robustness of our results by re-estimating our model and varying the proposed radius +10% (Table A6, Panel A) and -10% (Table A6, Panel B) compared to our benchmark case. Results are qualitatively similar to those in Table 4.

Overall, these mergers did not seem to pose any significant threat to the overall competitiveness of the market. For a variety of reasons, these mergers were either relatively small or had technical and scale efficiencies as targets, rather than market power. Nevertheless, we wanted to highlight that our proposed algorithm can identify significant differences in the product variety space, which in some markets can be an important strategic competition variable and one that affects consumer welfare.

6 Concluding Remarks

In this paper, we propose a new algorithm to identify the potential *ex post* effect of mergers by comparing outcomes of interest in areas of product overlap (the treated group) vis-à-vis areas of no overlap (the control group). The key concept of our empirical strategy is to take the geographic identification strategy that has been used widely across many retail markets and apply it in the product characteristics space. We utilize the idea of how “close” products are in terms of their characteristics to operationalize areas where the merging firms overlap versus those where they do not. Utilizing our proposed algorithm, researchers and policymakers can perform retrospective merger evaluation studies that look at the effects of mergers on both price and non-price aspects (in our application we measure product variety). We demonstrate the applicability and value of our algorithm by studying four mergers in the U.K. car market realized during the late 1980s and the 1990s.

Our work is also related to the small but growing literature that studies the impact of mergers on non-price-related decisions by firms. In particular, our work highlights the quite distinct differences in outcomes when we compare the two approaches, which often lead not just to different levels of statistical significance, but also to results with opposing signs. We also illustrate how differences in outcome cast additional light on the different strategic motivations for the mergers examined.

We acknowledge that our algorithm is incomplete in the sense that it only allows for a limited (three-)dimensional difference among products. However, we believe that this limitation can be overcome if one is willing to construct hedonic indices by grouping different characteristics. We also consider that more retrospective merger studies are needed both to evaluate the decisions of competition authorities but also to compare them with the *ex ante* predictions of various (structural or other) models. By drawing attention to an alternative algorithm we hope that we provide food for thought and will encourage researchers to develop new evaluative tools. The proposed method is less computation complex than alternative models, while also being transparent, flexible, and widely appliable to variety of markets where consumers have heterogeneous preferences over products' characteristics. We hope that because of these qualities great potential application by policy makers.

References

Aguzzoni, L., Argentesi, E., Ciari, L., Duso, T., & Tognoni, M. (2016). Ex post merger evaluation in the U.K. retail market for books. *Journal of Industrial Economics*, *64*(1), 170–200.

Allain, M. -L., Chambolle, C., Turolla, S., & Villas-Boas, S. (2017). The impact of retail mergers on food prices: Evidence from France. *Journal of Industrial Economics*, *65*(3), 469–509.

Amin, G.R., & Boamah (2021). A two-stage inverse data envelopment analysis approach for estimating potential merger gains in the US banking sector. *Managerial and Decision Economics*, 42(6),1454–1465.

Angrist, J. D., & Pischke, J. -S. (2010). The credibility revolution in empirical economics: How better research design is taking the con out of econometrics. *Journal of Economic Perspectives*, *24*(2), 3–30.

Argentesi, E., Buccirossi, P., Cervone, R., Duso, T., & Marrazzo, A. (2018). *Price or variety? An evaluation of mergers effects in grocery retailing*. DIW Berlin Discussion Paper No. 1734.

Ashenfelter, O., & Hosken, D. (2010). The effect of mergers on consumer prices: Evidence from five selected case studies. *Journal of Law and Economics, 53*(3), 417–466.

Ashenfelter, O. C., Hosken, D. S., & Weinberg, M. C. (2013). The price effects of a large merger of manufacturers: A case study of Maytag-Whirlpool. *American Economic Journal: Economic Policy*, *5*(1), 239–261.

Ashenfelter, O. C., Hosken, D. S., & Weinberg, M. C. (2015). Efficiencies brewed: Pricing and consolidation in the US beer industry. *RAND Journal of Economics*, *46*(2), 328–361.

Berry, S. T. (1994). Estimating discrete-choice models of product differentiation. *RAND Journal of Economics*, *25*(2), 242–262.

Berry, S. T., & Waldfogel, J. (2001). Do mergers increase product variety? Evidence from radio broadcasting. *Quarterly Journal of Economics*, *116*(3), 1009–1025.

Berry, S. T., Levinsohn, J., & Pakes, A. (1995). Automobile prices in market equilibrium. *Econometrica*, *63*(4), 841–890.

Berry, S. T., Levinsohn, J., & Pakes, A. (2004). Differentiated products demand systems from a combination of micro and macro data: The new car market. *Journal of Political Economy*, *112*(1), 68–105.

Björnerstedt, J., & Verboven, F. (2016). Does merger simulation work? Evidence from the Swedish analgesics market: Dataset. *American Economic Journal: Applied Economics*, *8*(3), 125–164.

Borenstein, S. (1990). Airline mergers, airport dominance, and market power. *American Economic Review*, *80*(2), 400–415.

Carlton, W. D. (2022, September 15). *How to make sensible merger policies?* Network Law Review. https://www.networklawreview.org/carlton-mergers/

Chiu, Y-H., Tai-Yu Lin, T-Y., Chang, T-H. Lin, Y-N., Shih-Yung Chiu, S-Y. (2021). Pre-valuating efficiency gains from potential mergers and acquisitions in the financial industry with the resample past–present–Future data envelopment analysis approach. *Managerial and Decision Economics*, 42(2), 369– 384.

Clark, K. B., & Fujimoto, T. (1991). *Product development performance: Strategy, organization, and management in the world auto industry*. Harvard University Press.

Connor, R. A., Feldman, R. D., & Dowd, B. E. (1998). The effects of market concentration and horizontal mergers on hospital costs and prices. *International Journal of the Economics of Business*, *5*, 159–180.

Cusumano, M. (1985). *The Japanese automobile industry*. Harvard University Press.

Dafny, L. S. (2009). Estimation and identification of merger effects: An application to hospital mergers. *Journal of Law and Economics, 52*(3), 523–550.

Danzon, P. M., Epstein, A., & Nicholson, S. (2007). Mergers and acquisitions in the pharmaceutical and biotech industries. *Managerial and Decision Economics*, *28*(4–5), 307–328.

Draganska, M., Mazzeo, M., & Seim, K. (2009). Beyond plain vanilla: Modelling joint product assortment and pricing decisions. *Quantitative Marketing and Economics*, *7*(2), 105–146.

Eckbo, B. E. (1983). Horizontal mergers, collusion and stockholder wealth. *Journal of Financial Economics*, *11*, 241–259.

Fan, Y. (2013). Ownership consolidation and product characteristics: A study of the US daily newspaper market. *American Economic Review*, *103*(5), 1598–1628.

Fan, Y., & Yang, C. (2020). Competition, product proliferation, and welfare: A study of the US smartphone market. *American Economic Journal: Microeconomics*, *12*(2), 99–134.

Gans and Hill (1997). Measuring Product Diversity. *Economics Letters*, 55(1), 145-150.

Gomes, E., Donnelly, T., Morris, D., & Collis, C. (2007). Improving merger process management skills over time: A comparison between the acquisition processes of Jaguar and of Land Rover by Ford. *Irish Management Journal*, *28*, 31–57.

Gould, B. (1998). The BMW acquisition of Rover. *The Antidote*, *3*(2), 37–38.

Hall, B. H. (1988). The effect of takeover activity on corporate research and development. In A. J. Auerbach (Ed.), *Corporate takeovers: Causes and consequences* (pp. 69–100). University of Chicago Press.

Hall, B. H. (1990). The impact of corporate restructuring on industrial research and development. In M. N. Baily & C. Winston (Eds.), *Brookings papers on economic activity: Microeconomics 1990* (pp. 85–135). Brookings Institution Press.

Hall, B. H. (1999). *Mergers and R&D revisited*. Prepared for the Quasi-Experimental Methods Symposium, Econometrics Laboratory, UC Berkeley.

Hastings, J. S. (2004). Vertical relationships and competition in retail gasoline markets: Empirical evidence from contract changes in Southern California. *American Economic Review*, *94*, 317–328.

Hausman, J. (1996) “Valuation of New Goods Under Perfect and Imperfect Competition”, in Bresnahan and Gordon eds., The Economics of New Goods, NBER.

Healy, P. M., Palepu, K. G., & Ruback, R. S. (1992). Does corporate performance improve after mergers? *Journal of Financial Economics*, *31*, 135–176.

Hitt, M., Hoskisson, R., Ireland, R. D., & Harrison, J. (1991). Are acquisitions a poison pill for innovation? *Academy of Management Journal*, *34*(3), 693–706.

Hitt, M., Hoskisson, R., Johnson, R. A., & Moesel, D. D. (1996). The market for corporate control and firm innovation. *Academy of Management Journal*, *39*(5), 1084–1119.

Jeziorski, P. (2014). Effects of mergers in two-sided markets: The US radio industry. *American Economic Journal: Microeconomics*, *6*(4), 35–73.

Kim, E. H., & Singal, V. (1993). Mergers and market power: Evidence from the U.S. airline industry. *American Economic Review*, *83*, 549–569.

Lancaster, J. (1971). *Consumer demand: A new approach*. Columbia University Press.

Laux, J. M. (1992). *The European automobile industry*. Twayne Publishers.

Mazzeo, M., Seim, K., & Varela, M. (2018). The welfare consequences of mergers with endogenous product choice. *Journal of Industrial Economics*, *66*(4), 980–1016.

McCabe, M. (2002) Journal pricing and mergers: A portfolio approach. *American Economic Review*, *92*(1), 269–289.

Nevo, A., & Whinston, M. D. (2010). Taking the dogma out of econometrics: Structural modeling and credible inference. *Journal of Economic Perspectives*, *24*(2), 69–82.

Ormosi, P., Mariuzzo, F., Havell, R., Fletcher, A., & Lyons, B. (2015). *A review of merger decisions in the EU: What can we learn from ex-post evaluations?* European Commission.

Ornaghi, C. (2009). Mergers and innovation in big pharma. *International Journal of Industrial Organization*, *27*(1), 70–79.

Panetta, F., & Focarelli, D. (2003). Are mergers beneficial to consumers? Evidence from the Italian market for bank deposits. *American Economic Review*, *93*(4), 1152–1167.

Peters, C. (2006). Evaluating the performance of merger simulations: Evidence from the U.S. airline industry. *Journal of Law and Economics*, *49*(2), 627–635.

Petrin, A. (2002). Quantifying the benefits of new products: The case of the minivan. *Journal of Political Economy*, *110*(4), 705–729.

Pinkse and Slade (2004). Mergers, brand competition, and the price of a pint. *European Economic Review*, 48(3), 617-643.

Prabhu, J. C., Chandy, R. K., & Ellis, M. (2005). The impact of acquisitions on innovation: Poison pill, placebo, or tonic? *Journal of Marketing*, *69*(1), 114–130.

Ravenscraft, D. J., & Scherer, F. M. (1987). *Mergers, sell-offs and economic efficiency*. Brookings Institution Press.

Rubenstein, J. M. (1992). *The changing US auto industry: A geographical analysis*. Routledge.

Rudholm, N. (2006). *Mergers and economies of scale: Volkswagen AG 1976–2000*. Department of Business Administration and Economics, University of Gävle.

Sweeting, A. (2010). The effects of mergers on product positioning: Evidence from the music radio industry. *RAND Journal of Economics*, *41*(2), 372–397.

Taylor, C. T., & Hosken, D. S. (2007). The economic effects of the Marathon-Ashland joint venture: The importance of industry supply shocks and vertical market structure. *Journal of Industrial Economics*, *55*(3), 419–451.

Verboven, F. (1996). International price discrimination in the European car market. *RAND Journal of Economics*, *27*(2), 240–268.

Walters, J. (2000, March 26). *How brash BMW ran Rover to catastrophe*. The Guardian. http://www.theguardian.com/business/2000/mar/26/rover.observerbusiness

Weinberg, M. C., & Hosken, D. S. (2013). Evidence on the accuracy of merger simulations. *Review of Economics and Statistics*, *95*(5), 1584–1600.

Wollmann, T. (2018). Trucks without bailouts: Equilibrium product characteristics for commercial vehicles. *American Economic Review*, *108*(6), 1364–1406.

TABLE 1 - SUMMARY STATISTICS

Variable	Mean	Standard Deviation	Median	10th percentile	90th percentile
PANEL A - MARKET OVERALL					
Price (real market prices adjusted to 2014)	30,368	24,432	23,927	14,057	49,121
Power (= horse power / weight)	94,791	33,320	88,235	59,184	136,000
Size (= length × width)	77	12	77	63	93
Cc (= engine capacity measured in cubic-inches)	2,020	854	1,836	1,288	2,969
Mpproad (= miles per pound in real 2014 prices)	47	12	47	32	62
Inject	1	0.499	1	0	1
Diesel	0	0.354	0	0	1
Turbo	0	0.332	0	0	1
PANEL B - MINI/SUPERMINI SEGMENT					
Price (real market prices adjusted to 2014)	14,593	3,568	14,442	10,041	18,988
Power (= horse power / weight)	77,237	22,266	71,615	57,447	110,714
Size (= length × width)	62	7	63	52	69
Cc (= engine capacity measured in cubic-inches)	1,272	285	1,275	954	1,686
Mpproad (= miles per pound in real 2014 prices)	57	10	56	45	68
Inject	0	0.474	0	0	1
Diesel	0	0.305	0	0	1
Turbo	0	0.233	0	0	0
PANEL C - SMALL SEGMENT					
Price (real market prices adjusted to 2014)	19,348	4,745	19,195	13,863	24,988
Power (= horse power / weight)	83,887	23,106	80,702	58,366	115,481
Size (= length × width)	71	7	69	63	81
Cc (= engine capacity measured in cubic-inches)	1,582	255	1,590	1,295	1,969
Mpproad (= miles per pound in real 2014 prices)	52	9	51	40	63
Inject	0	0.49	0	0	1
Diesel	0	0.349	0	0	1
Turbo	0	0.258	0	0	0
PANEL D - MEDIUM SEGMENT					
Price (real market prices adjusted to 2014)	25,993	7,981	24,248	18,189	35,893
Power (= horse power / weight)	92,583	23,944	89,286	64,463	124,000
Size (= length × width)	79	7	80	70	87
Cc (= engine capacity measured in cubic-inches)	1,900	341	1,896	1,587	2,387
Mpproad (= miles per pound in real 2014 prices)	49	10	49	38	62
Inject	1	0.497	1	0	1
Diesel	0	0.38	0	0	1
Turbo	0	0.342	0	0	1
PANEL E - EXECUTIVE SEGMENT					
Price (real market prices adjusted to 2014)	38,686	10,825	37,210	26,705	51,216
Power (= horse power / weight)	104,204	25,091	102,069	75,342	134,541
Size (= length × width)	89	7	90	79	97
Cc (= engine capacity measured in cubic-inches)	2,427	487	2,383	1,985	2,972
Mpproad (= miles per pound in real 2014 prices)	42	8	41	33	54
Inject	1	0.445	1	0	1
Diesel	0	0.378	0	0	1
Turbo	0	0.404	0	0	1
PANEL F - LUXURY SEGMENT					
Price (real market prices adjusted to 2014)	91,500	51,185	75,224	49,257	172,308
Power (= horse power / weight)	142,048	36,500	135,635	103,485	167,598
Size (= length × width)	97	7	98	87	108
Cc (= engine capacity measured in cubic-inches)	4,259	1,255	3,980	2,799	6,748
Mpproad (= miles per pound in real 2014 prices)	32	6	32	24	40
Inject	1	0.414	1	0	1
Diesel	0	0	0	0	0
Turbo	0	0.189	0	0	0
PANEL G - SPORTS SEGMENT					
Price (real market prices adjusted to 2014)	50,371	39,417	36,463	21,278	96,668
Power (= horse power / weight)	137,041	44,535	128,906	87,685	199,245
Size (= length × width)	77	13	77	64	86
Cc (= engine capacity measured in cubic-inches)	2,512	1,061	2,144	1,587	3,947
Mpproad (= miles per pound in real 2014 prices)	40	9	40	29	51
Inject	1	0.451	1	0	1
Diesel	0	0.082	0	0	0
Turbo	0	0.333	0	0	1
PANEL H - 4×4 SEGMENT					
Price (real market prices adjusted to 2014)	37,385	18,052	33,990	22,492	54,755
Power (= horse power / weight)	74,141	21,606	70,892	50,562	103,015
Size (= length × width)	80	12	81	64	94
Cc (= engine capacity measured in cubic-inches)	2,795	827	2,746	1,590	3,964
Mpproad (= miles per pound in real 2014 prices)	31	6	30	23	40
Inject	0	0.498	0	0	1
Diesel	0	0.483	0	0	1
Turbo	0	0.448	0	0	1
PANEL I - PERSONAL CARRIER SEGMENT					
Price (real market prices adjusted to 2014)	31,179	9,576	29,186	22,270	43,452
Power (= horse power / weight)	82,569	27,686	79,727	54,545	102,542
Size (= length × width)	84	11	85	71	98
Cc (= engine capacity measured in cubic-inches)	2,087	415	1,998	1,755	2,792
Mpproad (= miles per pound in real 2014 prices)	40	7	38	31	51
Inject	1	0.463	1	0	1
Diesel	0	0.436	0	0	1
Turbo	0	0.438	0	0	1

Notes: Summary statistics of the key automobile charactersitics of the data by market segment anf for the overall market.
Source: Authors' calculations based on price data taken from Parkers' Guide to New and Used Prices', the Motorists' Guide to New and Used Car Prices' and car attributes data from Augur-Tech Ltd.

TABLE 2 - SUMMARY STATISTICS OF THE NUMBER OF CAR MODELS

Number of car models in	Mean	Standard Deviation	Median	10th percentile	90th percentile
Market overall	536	80	556	411	628
Mini/Super-mini	84	12	81	69	99
Small Family	111	9	108	100	125
Medium	152	21	152	118	176
Executive	68	13	72	48	86
Luxury	23	4	24	15	28
Sports	53	8	50	44	62
4×4	38	18	35	14	58
Personal carrier	33	22	27	6	67

Notes: Summary statistics of the key automobile charactersitics of the data by market segment anf for the overall market.
Source: Authors' calculations based on sales data from the Society of Motor Manufacturers and Traders and car attributes data from Augur Tech Ltd.

TABLE 3 - MERGER EFFECT ON PRICE

PANEL A. CAR SEGMENT CLASSIFICATION

			(1)	(2)	(3)	(4)
		Dependent variable	ln($Price_{it}$)	ln($Price_{it}$)	ln($Price_{it}$)	ln($Price_{it}$)
		Sample	Full sample	Acquiring	Acquired	Competitors
Acquiring	Acquired	Time window	(τ-1, τ+1)	(τ-1, τ+1)	(τ-1, τ+1)	(τ-1, τ+1)
VAG	Seat	$Post_t \times Overlap_i$	-0.012		0.017*	-0.014
			(0.015)		(0.010)	(0.015)
Ford	Jaguar	$Post_t \times Overlap_i$	0.021		0.035	0.017
			(0.016)		(0.021)	(0.018)
BMW	Austin-Rover	$Post_t \times Overlap_i$	0.008	0.021	-0.012	0.008
			(0.022)	(0.022)	(0.022)	(0.022)
Ford	Mazda	$Post_t \times Overlap_i$	0.013	0.027**	0.002	0.013
			(0.013)	(0.013)	(0.010)	(0.015)

PANEL B. CHARACTERISTICS SPACE CLASSIFICATION

			(1)	(2)	(3)	(4)
		Dependent variable	ln($Price_{it}$)	ln($Price_{it}$)	ln($Price_{it}$)	ln($Price_{it}$)
		Sample	Full sample	Acquiring	Acquired	Competitors
Acquiring	Acquired	Time window	(τ-1, τ+1)	(τ-1, τ+1)	(τ-1, τ+1)	(τ-1, τ+1)
VAG	Seat	$Post_t \times Overlap_i$	-0.031*	-0.026	0.006	-0.033*
			(0.016)	(0.054)	(0.014)	(0.016)
Ford	Jaguar	$Post_t \times Overlap_i$	0.014*	0.027**	0.037*	0.012
			(0.008)	(0.010)	(0.021)	(0.009)
BMW	Austin-Rover	$Post_t \times Overlap_i$	0.012	0.013	-0.025***	0.028*
			(0.014)	(0.008)	(0.008)	(0.014)
Ford	Mazda	$Post_t \times Overlap_i$	0.0004	0.029***	-0.025***	0.000
			(0.010)	(0.006)	(0.007)	(0.010)

Notes: The dependent variable is natural logarithm of real prices (1993-1999). Standard errors clustered at the brand level are reported in parentheses below coefficients: *significant at 10%; **significant at 5%; ***significant at 1%.
Source: Authors' calculations based on price data taken from Parkers' Guide to New and Used Prices and the Motorists' Guide to New and Used Car Prices, and car attributes data from Augur-Tech Ltd.

TABLE 4 - MERGER EFFECT ON PRODUCT VARIETY

PANEL A. CAR SEGMENT CLASSIFICATION

			(1)	(2)	(3)	(4)
		Dependent variable	ln(#models$_{it}$)	ln(#models$_{it}$)	ln(#models$_{it}$)	ln(#models$_{it}$)
		Sample	Full sample	Acquiring	Acquired	Competitors
Acquiring	Acquired	Time window	(τ-1, τ+3)	(τ-1, τ+3)	(τ-1, τ+3)	(τ-1, τ+3)
VAG	Seat	Post$_t$ × Overlap$_i$	-0.030	-0.440***	0.711***	-0.060
			(0.137)	(0.064)	(0.064)	(0.140)
Ford	Jaguar	Post$_t$ × Overlap$_i$	-0.072	-0.485*	0.064	-0.077
			(0.146)	(0.281)	(0.091)	(0.168)
BMW	Austin-Rover	Post$_t$ × Overlap$_i$	0.010	0.300***	0.410***	-0.028
			(0.088)	(0.066)	(0.066)	(0.091)
Ford	Mazda	Post$_t$ × Overlap$_i$	-0.124	-0.251	0.115	-0.119
			(0.090)	(0.165)	(0.090)	(0.094)

PANEL B. CHARACTERISTICS SPACE CLASSIFICATION

			(1)	(2)	(3)	(4)
		Dependent variable	ln(#models$_{it}$)	ln(#models$_{it}$)	ln(#models$_{it}$)	ln(#models$_{it}$)
		Sample	Full sample	Acquiring	Acquired	Competitors
Acquiring	Acquired		(τ-1, τ+3)	(τ-1, τ+3)	(τ-1, τ+3)	(τ-1, τ+3)
VAG	Seat	Post$_t$ × Overlap$_i$	-0.124	-0.064	0.815***	-0.183
			(0.157)	(0.156)	(0.112)	(0.158)
Ford	Jaguar	Post$_t$ × Overlap$_i$	0.171	-0.071	0.156	0.200
			(0.168)	(0.136)	(0.160)	(0.177)
BMW	Austin-Rover	Post$_t$ × Overlap$_i$	-0.105	-0.298**	-0.054	-0.140
			(0.189)	(0.121)	(0.176)	(0.180)
Ford	Mazda	Post$_t$ × Overlap$_i$	0.047	-0.609***	-0.551***	0.137
			(0.172)	(0.117)	(0.117)	(0.162)

Notes: The dependent variable is the natural logarithm of the number of models produced by each brand in control and treatment areas (1993-1999). Standard errors clustered at the brand level are reported in parentheses below coefficients: *significant at 10%; **significant at 5%; ***significant at 1%.
Source: Authors' calculations based on sales data from the Society of Motor Manufacturers and Traders, and car attributes data from Augur-Tech Ltd.

TABLE A1 - MERGER EFFECT ON PRICE (MARKET OVERALL)

	(1)	(2)	(3)	(4)
Dependent variable	$\ln(Price_{it})$	$\ln(Price_{it})$	$\ln(Price_{it})$	$\ln(Price_{it})$
Merger	Seat-Vag	Jaguar-Ford	Rover-BMW	Mazda-Ford
	PANEL A. CAR SEGMENT CLASSIFICATION			
$Treat_i \times Post_t$	-0.012	0.021	0.008	0.013
	(0.015)	(0.016)	(0.022)	(0.013)
Mpproad	-0.003	-0.001	0.002	-0.008*
(= miles per pound in real 2014 prices)	(0.003)	(0.006)	(0.003)	(0.005)
Inject	0.111***	-0.035***		0.128***
	(0.01)	(0.009)		(0.009)
Diesel	-0.014	0.038	-0.019**	
	(0.011)	(0.038)	(0.007)	
Turbo	0.043**	-0.082***		0.333***
	(0.02)	(0.006)		(0.02)
Manufactured in UK		-0.066***	-0.058**	0.119***
		(0.009)	(0.025)	(0.009)
Manufactured in West Germany		0.05***		
		(0.009)		
Manufactured in France			-0.04***	
			(0.012)	
Manufactured in Spain				-0.073***
				(0.018)
Observations	619	735	791	844
Within R^2	0.416	0.251	0.013	0.220
	PANEL B. CHARACTERISTICS SPACE CLASSIFICATION			
$Treat_i \times Post_t$	-0.031*	0.014*	0.012	0
	(0.016)	(0.008)	(0.014)	(0.01)
Mpproad	-0.008**	0.001	0.006*	-0.016**
(= miles per pound in real 2014 prices)	(0.003)	(0.006)	(0.004)	(0.007)
Inject		-0.042***		0.078***
		(0.009)		(0.013)
Diesel		-0.022	-0.048**	
		(0.031)	(0.018)	
Turbo	0.09***	-0.044	0.042***	
	(0.023)	(0.039)	(0.012)	
Manufactured in UK		-0.071***	0.041***	0.119***
		(0.009)	(0.006)	(0.007)
Manufactured in West Germany		0.042***	0.061***	
		(0.01)	(0.007)	
Observations	346	717	197	254
Within R^2	0.509	0.277	0.155	0.397
Brand Fixed Effects	YES	YES	YES	YES
Segment Fixed Effects	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES

Notes: The dependent variable is the natural logarithm of real prices. All equations include brand, segment and year fixed effects. Standard errors are clustered at the brand level and are reported in parentheses below coefficients. ***, **, * mark statistical significance at the 0.01, 0.05 and 0.10 level respectively.
Source: Authors' calculations based on price data taken from Parkers' Guide to New and Used Prices and the Motorists' Guide to New and Used Car Prices and car attributes data from Augur Tech Ltd.

TABLE A2 - MERGER EFFECT ON PRICE (EFFECT ON PARTIES)

	(1)	(2)	(3)	(4)
Dependent variable	$\ln(Price_{it})$	$\ln(Price_{it})$	$\ln(Price_{it})$	$\ln(Price_{it})$
Merger	Seat-Vag	Jaguar-Ford	Rover-BMW	Mazda-Ford
	PANEL A. CAR SEGMENT CLASSIFICATION			
$Competitors_i \times Post_t$	-0.012	0.021	0.008	0.013
	(0.015)	(0.016)	(0.022)	(0.013)
$Acquiring_i \times Post_t$			0.021	0.027**
			(0.022)	(0.013)
$Acquired_i \times Post_t$	0.017*	0.035	-0.012	0.002
	(0.01)	(0.021)	(0.022)	(0.01)
Mpproad	-0.003	-0.001	0.002	-0.008*
(= miles per pound in real 2014 prices	(0.003)	(0.006)	(0.003)	(0.005)
Inject	0.112***	-0.035***		0.129***
	(0.01)	(0.009)		(0.01)
Diesel	-0.014	0.039	-0.019**	
	(0.011)	(0.038)	(0.007)	
Turbo	0.043**	-0.082***		0.334***
	(0.02)	(0.006)		(0.022)
Manufactured in UK		-0.066***	-0.058**	0.105***
		(0.009)	(0.025)	(0.006)
Manufactured in France			-0.04***	
			(0.012)	
Manufactured in Spain				-0.1***
				(0.009)
Manufactured in West Germany		0.05***		
		(0.009)		
Observations	619	735	791	844
Within R^2	0.416	0.251	0.013	0.220
	PANEL B. CHARACTERISTICS SPACE CLASSIFICATION			
$Competitors_i \times Post_t$	-0.033*	0.012	0.028*	0
	(0.016)	(0.009)	(0.014)	(0.01)
$Acquiring_i \times Post_t$	-0.026	0.027**	0.013	0.029***
	(0.054)	(0.01)	(0.008)	(0.006)
$Acquired_i \times Post_t$	0.006	0.037*	-0.025***	-0.025***
	(0.014)	(0.021)	(0.008)	(0.007)
Mpproad	-0.008**	0.001	0.007**	-0.014*
(= miles per pound in real 2014 prices	(0.003)	(0.006)	(0.003)	(0.007)
Inject		-0.039***		
		(0.01)		
Diesel		-0.017	-0.051***	
		(0.031)	(0.016)	
Turbo	0.092***	-0.042	0.027**	
	(0.024)	(0.041)	(0.012)	
Manufactured in West Germany		0.042***	0.053***	
		(0.01)	(0.007)	
Manufactured in UK		-0.072***	0.049***	0.119***
		(0.009)	(0.007)	(0.007)
Manufactured in Spain				-0.077***
				(0.013)
Observations	346	717	197	254
Within R^2	0.511	0.281	0.268	0.422
Brand Fixed Effects	YES	YES	YES	YES
Segment Fixed Effects	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES

Notes: The dependent variable is the natural logarithm of real prices. All equations include brand, segment and year fixed effects. Standard errors are clustered at the brand level and are reported in parentheses below coefficients. ***, **, * mark statistical significance at the 0.01, 0.05 and 0.10 level respectively.

Source: Authors' calculations based on price data taken from Parkers' Guide to New and Used Prices and the Motorists' Guide to New and Used Car Prices and car attributes data from Augur Tech Ltd.

TABLE A3 - MERGER EFFECT ON VARIETY (EFFECT ON MARKET OVERALL)

	(1)	(2)	(3)	(4)
Dependent variable	ln(#models$_{it}$)	ln(#models$_{it}$)	ln(#models$_{it}$)	ln(#models$_{it}$)
Merger	Seat-Vag	Jaguar-Ford	Rover-BMW	Mazda-Ford
	PANEL A. CAR SEGMENT CLASSIFICATION			
$Treat_i \times Post_t$	-0.03	-0.072	0.01	-0.124
	(0.137)	(0.146)	(0.088)	(0.09)
$Treat_i$	-0.234	-0.673***	-0.048	0.407**
	(0.198)	(0.214)	(0.134)	(0.153)
Observations	364	410	488	565
Within R^2	0.473	0.519	0.467	0.451
	PANEL B. CHARACTERISTICS SPACE CLASSIFICATION			
$Treat_i \times Post_t$	-0.124	0.171	-0.105	0.047
	(0.157)	(0.168)	(0.189)	(0.172)
$Treat_i$	-0.1	-0.021	0.392	0.153
	(0.205)	(0.265)	(0.246)	(0.188)
Observations	185	249	150	190
Within R^2	0.680	0.631	0.743	0.671
Brand Fixed Effects	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES

Notes: The dependent variable is the natural logarithm of the number of models produced by each brand in control and treatment areas (1993-1999). All equations include brand and year fixed effects. Standard errors are clustered at the brand level and are reported in parentheses below coefficients. ***, **, * mark statistical significance at the 0.01, 0.05 and 0.10 level respectively.

Source: Authors' calculations based on sales data from the Society of Motor Manufacturers and Traders and car attributes data from Augur Tech Ltd.

TABLE A4 - MERGER EFFECT ON VARIETY (EFFECT ON PARTIES)

	(1)	(2)	(3)	(4)
Dependent variable	$\ln(\#models_{it})$	$\ln(\#models_{it})$	$\ln(\#models_{it})$	$\ln(\#models_{it})$
Merger	Seat-Vag	Jaguar-Ford	Rover-BMW	Mazda-Ford
	PANEL A. CAR SEGMENT CLASSIFICATION			
$Competitors_i \times Post_t$	-0.06	-0.077	-0.028	-0.119
	(0.14)	(0.168)	(0.091)	(0.094)
$Acquiring_i \times Post_t$	-0.44***	-0.485*	0.3***	-0.251
	(0.064)	(0.281)	(0.066)	(0.165)
$Acquired_i \times Post_t$	0.711***	0.064	0.41***	0.115
	(0.064)	(0.091)	(0.066)	(0.09)
Observations	364	410	488	565
Within R^2	0.494	0.538	0.470	0.453
	PANEL B. CHARACTERISTICS SPACE CLASSIFICATION			
$Competitors_i \times Post_t$	-0.183	0.2	-0.14	0.137
	(0.158)	(0.177)	(0.18)	(0.162)
$Acquiring_i \times Post_t$	-0.064	-0.071	-0.298**	-0.609***
	(0.156)	(0.136)	(0.121)	(0.117)
$Acquired_i \times Post_t$	0.815***	0.156	-0.054	-0.551***
	(0.112)	(0.16)	(0.176)	(0.117)
Observations	185	249	150	190
Within R^2	0.737	0.657	0.822	0.753
Brand Fixed Effects	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES

Notes: The dependent variable is the natural logarithm of the number of models produced by each brand in control and treatment areas (1993-1999). All equations include brand and year fixed effects. Standard errors are clustered at the brand level and are reported in parentheses below coefficients. ***, **, * mark statistical significance at the 0.01, 0.05 and 0.10 level respectively.

Source: Authors' calculations based on sales data from the Society of Motor Manufacturers and Traders and car attributes data from Augur Tech Ltd.

TABLE A5 - MERGER EFFECT ON PRICE - ROBUSTNESS

PANEL A. CHARACTERISTICS SPACE CLASSIFICATION (+10% RADIUS)

			(1)	(2)	(3)	(4)
		Dependent variable	$\ln(Price_{it})$	$\ln(Price_{it})$	$\ln(Price_{it})$	$\ln(Price_{it})$
		Sample	Full sample	Acquiring	Acquired	Competitors
Acquiring	Acquired	Time window	(τ-1, τ+1)	(τ-1, τ+1)	(τ-1, τ+1)	(τ-1, τ+1)
VAG	Seat	$Post_t \times Overlap_i$	-0.019	0.022	0.010	-0.025
			(0.014)	(0.021)	(0.015)	(0.015)
Ford	Jaguar	$Post_t \times Overlap_i$	0.012	0.026**	0.037*	0.010
			(0.008)	(0.010)	(0.021)	(0.009)
BMW	Austin-Rover	$Post_t \times Overlap_i$	0.014	0.016*	-0.017*	0.027*
			(0.013)	(0.008)	(0.009)	(0.014)
Ford	Mazda	$Post_t \times Overlap_i$	-0.005	0.029***	-0.028***	-0.007
			(0.011)	(0.007)	(0.007)	(0.009)

PANEL B. CHARACTERISTICS SPACE CLASSIFICATION (-10% RADIUS)

			(1)	(2)	(3)	(4)
		Dependent variable	$\ln(Price_{it})$	$\ln(Price_{it})$	$\ln(Price_{it})$	$\ln(Price_{it})$
		Sample	Full sample	Acquiring	Acquired	Competitors
Acquiring	Acquired	Time window	(τ-1, τ+1)	(τ-1, τ+1)	(τ-1, τ+1)	(τ-1, τ+1)
VAG	Seat	$Post_t \times Overlap_i$	-0.016	0.064**	0.024*	-0.024
			(0.015)	(0.014)	(0.013)	(0.015)
Ford	Jaguar	$Post_t \times Overlap_i$	0.023**	0.029***	0.045	0.021*
			(0.010)	(0.011)	(0.030)	(0.011)
BMW	Austin-Rover	$Post_t \times Overlap_i$	-0.000	0.000	-0.041***	0.018
			(0.012)	(0.004)	(0.009)	(0.015)
Ford	Mazda	$Post_t \times Overlap_i$	0.008	0.034***	-0.024***	0.009
			(0.010)	(0.007)	(0.007)	(0.010)

Notes: The dependent variable is natural logarithm of real prices (1993-1999). Standard errors clustered at the brand level are reported in parentheses below coefficients: *significant at 10%; **significant at 5%; ***significant at 1%.

Source: Authors' calculations based on price data taken from Parkers' Guide to New and Used Prices and the Motorists' Guide to New and Used Car Prices, and car attributes data from Augur-Tech Ltd.

TABLE A6 - MERGER EFFECT ON PRODUCT VARIETY - ROBUSTNESS

PANEL A. CHARACTERISTICS SPACE CLASSIFICATION (+10% RADIUS)

			(1)	(2)	(3)	(4)
		Dependent variable	ln(#models$_{it}$)	ln(#models$_{it}$)	ln(#models$_{it}$)	ln(#models$_{it}$)
		Sample	Full sample	Acquiring	Acquired	Competitors
Acquiring	Acquired	Time window	(τ-1, τ+3)	(τ-1, τ+3)	(τ-1, τ+3)	(τ-1, τ+3)
VAG	Seat	$Post_t \times Overlap_i$	-0.261	-0.370***	0.686***	-0.298*
			(0.155)	(0.128)	(0.099)	(0.159)
Ford	Jaguar	$Post_t \times Overlap_i$	-0.038	0.050	0.253	0.123
			(0.175)	(0.167)	(0.204)	(0.202)
BMW	Austin-Rover	$Post_t \times Overlap_i$	-0.001	-0.167	0.064	-0.045
			(0.208)	(0.131)	(0.163)	(0.205)
Ford	Mazda	$Post_t \times Overlap_i$	0.015	-0.625***	-0.561***	0.079
			(0.167)	(0.112)	(0.112)	(0.162)

PANEL B. CHARACTERISTICS SPACE CLASSIFICATION (-10% RADIUS)

			(1)	(2)	(3)	(4)
		Dependent variable	ln(#models$_{it}$)	ln(#models$_{it}$)	ln(#models$_{it}$)	ln(#models$_{it}$)
		Sample	Full sample	Acquiring	Acquired	Competitors
Acquiring	Acquired		(τ-1, τ+3)	(τ-1, τ+3)	(τ-1, τ+3)	(τ-1, τ+3)
VAG	Seat	$Post_t \times Overlap_i$	0.005	-0.160	0.651***	-0.031
			(0.168)	(0.113)	(0.113)	(0.174)
Ford	Jaguar	$Post_t \times Overlap_i$	0.258	-0.158	0.077	0.280*
			(0.157)	(0.147)	(0.195)	(0.166)
BMW	Austin-Rover	$Post_t \times Overlap_i$	-0.080	-0.343**	-0.127	-0.053
			(0.200)	(0.150)	(0.208)	(0.186)
Ford	Mazda	$Post_t \times Overlap_i$	-0.012	-0.712***	-0.733***	0.074
			(0.191)	(0.116)	(0.116)	(0.190)

Notes: The dependent variable is the natural logarithm of the number of models produced by each brand in control and treatment areas (1993-1999). Standard errors clustered at the brand level are reported in parentheses below coefficients: *significant at 10%; **significant at 5%; ***significant at 1%.
Source: Authors' calculations based on sales data from the Society of Motor Manufacturers and Traders, and car attributes data from Augur-Tech Ltd.

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