Ex Post Merger Analysis in the Car Market and the Role of Conduct*

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Abstract

We take a new perspective on evaluating past mergers by departing from the assumption of Bertrand conduct. Our dataset, spanning thirty years (1970-1999) over five European countries, allows us to estimate flexible forms of conduct or inter firm coordination. We find some evidence for coordination, especially for firms with large market shares and firms operating in their domestic market. We look at the merger between Fiat and Alfa Romeo in 1986, to investigate the role of conduct in rationalizing post merger price evolutions. We find that assuming Bertrand conduct leads to an overestimation of realized cost efficiencies. Furthermore, if conduct differs over countries, a Bertrand model would incorrectly suggest cost efficiencies in countries where there is more coordination between firms.

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1 Introduction

It is common knowledge that coordination between competing firms is more likely to arise in concentrated markets. Therefore, whenever assessing mergers in such markets, it is not obvious which assumptions about industry conduct are justifiable. This assumption however has an important impact when evaluating mergers and therefore deserves thorough consideration. For instance the outcome of a merger would drastically differ between a market where competition is fierce - and the market power effect is significant - compared to a market where firms fully coordinate on prices - where the market power effect is de facto limited. Despite its importance, there have not been many attempts at directly estimating conduct in the context of a merger case.

Using a dataset spanning five countries and thirty years, we contribute to the conduct literature by directly estimating conduct and analyzing its impact on ex post merger evaluation results. We review the merger between Fiat and Alfa Romeo in 1986. This case is a very unique opportunity, since there are major differences in market structure surrounding the merging firms in the countries we observe. We exploit this variation by estimating flexible patterns of conduct, allowing for conduct to vary over countries and years. We then disentangle the effects of conduct and cost efficiencies and contrast our results with a standard conduct assumption in the literature, Bertrand competition.

To better understand the role of conduct, we start from the presumption that cost efficiencies from the merger should be equal across countries. This is very reasonable since the merging firms make use of the same plants for different destination markets, so that any cost efficiencies are likely to be common across markets. This assumption enables us to evaluate the role of conduct. In particular, a Bertrand model would predict high markup increases in markets where the merging firms gain significant unilateral market power and low markup increases in markets where the merging firms gain only limited market power. If actual prices are affected similarly in all markets, the Bertrand model would imply a larger cost efficiency in the markets with strong increased market power, which is not realistic. Accounting for the possibility of conduct leads to more realistic results. Merging firms could for instance already be coordinating more in markets where they have higher market shares before the merger, thus limiting the market power increase predicted by the Bertrand model.

The use of the Bertrand model in merger literature was popularised by Hausman et al. (1994) and Werden and Froeb (1994). While it has proven to be useful (Nevo, 2000a; Pinkse and Slade, 2004; Björnerstedt and Ver-
boven, 2015), some authors have found discrepancies between predictions from merger simulations and their ex post studies of price evolution (Peters, 2006; Weinberg and Hosken, 2013). In his paper, Peters decomposes the difference between the simulation and the observed price changes and finds that it is mainly explained by "unobserved supply-side changes" such as cost efficiencies and conduct, particularly suggesting that conduct might play a role. Weinberg and Hosken come to a similar conclusion when testing whether the Bertrand model fits their data. This is a prime reason to look into estimating conduct.

Similar to Ashenfelter and Hosken (2008), we use a difference-in-difference procedure to isolate post-merger changes in price and marginal costs, calculated on the assumption of Bertrand conduct. In order to estimate and fully understand the role of conduct, given the observed merger outcome, we build a structural model. On the demand side we estimate a BLP random coefficients model (Berry, Levinsohn and Pakes, 1995). The strength of this model is that it accounts for heterogeneity in consumer preferences, which enables us to estimate realistic substitution patterns between different car models. On the supply side we use an oligopoly model to calculate marginal costs, given the own- and cross-price elasticities retrieved from the demand model. Similar to a suggestion by Verboven (1996), our oligopoly model adapts the Bertrand model to include a set of conduct parameters, representing the degree to which firms internalize each others’ profits, and thus coordinate on prices. Upon an assumption of a marginal cost function, we are able to estimate these conduct parameters along with cost parameters.

Our paper indeed finds some evidence for conduct departing from the Bertrand assumption. In line with Besanko et al. (1996) and Carlton and Perloff (1994), who mention high concentration as a condition for sustainable coordination, especially firms with high market shares and operating in their domestic market seem to be inclined to coordinate their pricing behavior. These findings help in interpreting the observed effects on prices in different countries after the merger between Fiat and Alfa Romeo. When using a standard Bertrand model to rationalize price effects by the implied cost efficiencies, results suggest that firms realize different cost efficiencies in different markets. However, if we account for possible differences in conduct, driven by a difference in market structure, we find that cost efficiencies are more uniform across markets.

This paper is closely related to other papers estimating conduct. Sudhir (2001) estimates conduct parameters for each segment of the car market in order to compare the intensity of competition over segments. Ciliberto and Williams (2014) investigate the influence of multi-market contact between firms on the possibility of coordinated behavior. Lastly, and most
closely related to our paper, Miller and Weinberg (2015), investigate the link between mergers and the rise of tacit collusion. The contribution of our paper, compared to these, lies in the fact that we observe multiple geographic markets. Since concentration and conduct can differ between markets, our dataset presents us a unique opportunity to disentangle the roles of a unilateral increase in market power, conduct and cost efficiencies surrounding a merger. Since the unilateral increase in market power and Bertrand conduct are usually assumed in the merger literature, it follows that whatever residual variation is left to explain, is explained by cost efficiencies. By allowing conduct to differ\[1\] we are able to explain this variation by a mix of conduct differences and cost efficiencies. Further, we are the first to explicitly consider the impact of using the Bertrand conduct assumption in ex post merger evaluation, comparing it with our estimated forms of conduct.

The paper is organized into seven sections. Section 2 discusses the background of the merger between Alfa Romeo and Fiat. Section 3 introduces the Bertrand framework and discusses the results of using it for merger analysis. Section 4 outlines our structural model for estimating conduct. Section 5 discusses estimation and identification details. Section 6 presents the results of our demand and conduct estimation. Section 7 concludes.

2 Merger Background and Data\[2\]

We study the merger between Fiat and Alfa Romeo, which took place in 1986. This is an interesting merger case because both firms’ market share varies greatly over countries. Further, both firms originate from the same country, which is interesting given the documented consumer bias for domestic cars. By the time both firms merged, Fiat had been the market leader in Italy for a long time and it had already acquired other Italian brands Autobianchi in 1968 and Lancia and Ferrari in 1969. Therefore, Alfa Romeo was the only sizeable competitor to Fiat within Italy.\[3\]

\[1\]In theory, our model could even allow for different assumptions about the unilateral increase in market power. As Michel (2013) mentions, it is possible that merged firms do not fully internalize each others’ profits after the merger (because of conflicting incentive structures, delayed harmonization, etc.). In that case, the unilateral increase in market power is overestimated when assuming full profit internalization.


\[3\]The largest Italian competitor left was Innocenti with a market share of approximately 0.5%.
Alfa Romeo, still the second firm in terms of market share in the Italian market in 1985, had been part of IRI (Instituto per la Riconstruzione Industriale), an Italian public holding company, since 1933. It suffered from financial problems since the oil crisis of 1973-1974 and after five years without profit, in 1980, it signed a deal with Nissan to establish a joint venture in which both had a 50% stake. This joint venture resulted in the production of the Alfa Romeo Arna. Notable is that the 1980 strategic plan also involved an agreement with the Fiat group for the production of common components. The Arna was considered a failure and after repeated reorganizations and strategic plans, Alfa was still incurring losses in 1984 and 1985. The company got capital injections from the Italian government in 1985 and 1986, in order to cover losses incurred by the company in 1984 and the first half of 1985, as well as subsidies and soft loans during this period for innovative investments and R&D expenses.

The decision to sell the motor vehicle activities of the Alfa Romeo Group was the result of a series of assessments of future strategy given that the 1980 restructuring plan had proved a failure. These assessments were carried out in 1985 and 1986 both directly by Finmeccanica, the mechanical holdings arm of IRI, the IRI itself and by the appropriate government and parliamentary bodies. They showed that the Group could not become profitable as an independent producer and that the only possible solution to Alfa Romeo’s deepening financial and market crisis was to merge the company with a large motor vehicle manufacturer. Negotiations were held with Fiat as well as with Ford, but Finmeccanica chose Fiat over Ford, since, among other reasons, it showed a stronger commitment to employment objectives and the Alfa Romeo product range would be renewed more rapidly, offering a better guarantee that it would attain a reasonable level of competitiveness on the European market within a fairly short period of time.

In this paper we rely on a dataset containing information on sales, prices

<table>
<thead>
<tr>
<th></th>
<th>Fiat</th>
<th>Alfa Romeo</th>
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<tbody>
<tr>
<td>Belgium</td>
<td>3.8%</td>
<td>0.7%</td>
</tr>
<tr>
<td>France</td>
<td>5.4%</td>
<td>0.7%</td>
</tr>
<tr>
<td>Germany</td>
<td>4.6%</td>
<td>0.3%</td>
</tr>
<tr>
<td>Italy</td>
<td>52.8%</td>
<td>6.5%</td>
</tr>
<tr>
<td>UK</td>
<td>3.1%</td>
<td>0.1%</td>
</tr>
</tbody>
</table>

Note: Observed market shares for Fiat and Alfa Romeo in 1985.
and characteristics of the car models sold in Belgium, France, Germany, Italy and the United Kingdom during the period 1970-1999. The total number of observations is 12,873, implying about 85 models on average are sold in each market each year. For each car model, we have data about engine attributes (horsepower, displacement), dimensions (weight, length, width, height) and performance variables (fuel consumption, acceleration time, maximum speed), collected from publicly available sources. The price data are list prices corresponding to the base model available in the market, as published in consumer catalogues. Sales are new car registrations for the model range. In addition, we make use of information on each model’s origin, production location, brand ownership and market segment (or ”class”). Finally, the dataset also contains macroeconomic variables including population, exchange rates, GDP, and consumer price indices. Goldberg and Verboven (2001) provide a more detailed description the dataset and its sources, although they only use part of the data from 1980-1993.

Table 1 displays the market shares of the merging firms in the year prior to the merger. As is clear from the table, the manufacturers have larger market shares in their home markets. Since both firms have the same origins, it is interesting to see how differences in market shares over markets translate into observed merger effects.

3 Merger Analysis under Bertrand-Nash

In this section we first consider the impact of the merger on prices in the five different markets. We then compare this with the impact on the estimated marginal cost, under the assumption that firms behave as multiproduct Bertrand competitors. This comparison serves to emphasize the necessity of accounting for the role of conduct in analyzing the merger effects. Indeed, we can examine whether the Bertrand model is consistent with comparable cost efficiencies across countries (as one would expect) or whether it implies different cost efficiencies, which would stress the need for accounting for different forms of conduct.

In our analysis of the merger, we can exploit the fact that we have data from the period after the merger to conduct an ex-post analysis of prices and marginal costs. We start by inferring the observed price changes, using a difference-in-difference specification related to Ashenfelter and Hosken (2008):

$$\ln(p_{jt}) = \beta_1 c(post_t * MP_j) + \beta_2 x_{jt} + \beta_3 trend_t + \gamma_c + \epsilon_{jt} \quad (1)$$

where $j$ indexes car models, $c$ indexes countries and $t$ indexes markets (de-
fined as year/country combinations throughout this paper). Price is indicated by \( p_{jt} \), \( post_t \) is a dummy set to one in the post-merger period, and \( MP_j \) equals one if model \( j \) belongs to one of the merging parties. The country specific \( \beta_{1,c} \) therefore measures the mergers’ price effect in country \( c \), \( x_{jt} \) is a vector of characteristics and \( \epsilon \) is the error term. In order to isolate the price effects in different countries, we need to add some controls. We control for general industry wide evolutions with a time trend and for differences between countries with country fixed effects \( \gamma_c \). Further we add controls in \( x_{jt} \) for possible different post merger time effects between countries by adding \( Post_t \ast country_c \) dummies; and for possible constant price differences of the merged firm between countries by including \( MP_j \ast country_c \) dummies.

If we assume that the merger does not affect the prices of the merged firm’s competitors, the competitors are a valid control group in a difference-in-difference approach. Because we control for the general price change after the merger and persistent price differences, the \( \beta_{1,c} \) coefficients only measure the difference between the price increase of the merged firm’s products relative to the control group. This specification thus successfully isolates the effect of the merger on the merged firm’s prices, to be interpreted as percent change in price. Björnerstedt and Verboven (2015) point out that even if the merger does raise prices of the merged firm’s competitors, \( \beta_{1,c} \), which is the difference in price change between the merged firm and its competitors, may be interpreted as a lower bound for the merger price effect.

It is possible to calculate the marginal costs that rationalize price evolutions, based upon an assumption of conduct. In the merger literature, it is common to assume oligopolistic firms compete in a Bertrand-Nash fashion. In this case, the profit maximization problem of firm \( f \) with portfolio \( F_f \) in a market \( t \) with \( F \) firms is defined by

\[
\Pi_f = \sum_{j \in F_f} (p_{jt} - mc_{jt}) s_{jt}(p_t) M
\]

where \( M \) is the market size, \( s_{jt}(p) \) is market share as a function of prices and \( mc_{jt} \) is the constant marginal cost of production.

Rewriting the first order conditions for profit maximization in vector notation, we are able to calculate marginal costs:

\[
mc_t = p_t + \Delta_t(\theta_d)^{-1} s_t(p_t).
\]

\( \Delta_t(\theta_d) \) can be calculated using \( \Omega_{t,jr} = \partial s_{rt}(p_t)/\partial p_{jt} \), a matrix of own and cross-price derivatives of market shares based on our demand estimates, and
an ownership matrix $\mathcal{H}_t$. It is defined as

$$\Delta_t(\theta_d) = \mathcal{H}_t \odot \Omega_t, \quad \text{with} \quad \mathcal{H}_{t,jr} = \begin{cases} 1, & \text{if } \exists f : \{j, r\} \subset F_f, \\ 0, & \text{otherwise}. \end{cases}$$ (4)

Similar to our analysis of price evolution, we can use a difference-in-difference approach to track the evolution of marginal costs as implied by the Bertrand oligopoly model.

$$ln(mc_{jt}) = \beta_{1,c}(\text{post}_t * MP_j) + \beta_{2}x_{jt} + \beta_{3}\text{trend}_t + \gamma_c + \omega_{jt}.$$ (5)

Table 2: Price and marginal cost effects assuming Bertrand

<table>
<thead>
<tr>
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<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
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<tbody>
<tr>
<td></td>
<td>log(price)</td>
<td>log(price)</td>
<td>log(mc)</td>
<td>log(mc)</td>
</tr>
<tr>
<td>post*MP</td>
<td>-0.021 (0.016)</td>
<td></td>
<td>-0.056 (0.018)</td>
<td></td>
</tr>
<tr>
<td>post<em>MP</em>Belgium</td>
<td>0.026 (0.032)</td>
<td>0.023 (0.036)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>post<em>MP</em>France</td>
<td>0.009 (0.033)</td>
<td>-0.003 (0.036)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>post<em>MP</em>Germany</td>
<td>-0.032 (0.036)</td>
<td>-0.052 (0.039)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>post<em>MP</em>Italy</td>
<td>-0.039 (0.032)</td>
<td>-0.144 (0.035)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>post<em>MP</em>UK</td>
<td>0.044 (0.035)</td>
<td>0.035 (0.038)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>log(hp/we)</td>
<td>0.667 (0.018)</td>
<td>0.659 (0.017)</td>
<td>0.848 (0.020)</td>
<td>0.842 (0.019)</td>
</tr>
<tr>
<td>log(width)</td>
<td>2.411 (0.080)</td>
<td>2.398 (0.074)</td>
<td>3.547 (0.089)</td>
<td>3.517 (0.082)</td>
</tr>
<tr>
<td>log(fuel)</td>
<td>1.013 (0.025)</td>
<td>1.023 (0.023)</td>
<td>1.040 (0.027)</td>
<td>1.052 (0.025)</td>
</tr>
<tr>
<td>domestic</td>
<td>0.044 (0.008)</td>
<td>0.052 (0.008)</td>
<td>0.011 (0.009)</td>
<td>0.030 (0.009)</td>
</tr>
<tr>
<td>constant</td>
<td>-8.045 (0.410)</td>
<td>-8.088 (0.379)</td>
<td>-13.544 (0.452)</td>
<td>-13.514 (0.417)</td>
</tr>
</tbody>
</table>

R2                   | 0.8206             | 0.8480             | 0.8493             | 0.8724             |

Note: 6118 observations for the sample 1979-1992. Estimation based on equation (1) with a All columns include country fixed effects and a time trend. Column 1 and 3 include Post, and $MP_j$ dummies, and column 2 and 4 include $\sum c(Post_t \times \text{country}_c)$ and $\sum c(MP_j \times \text{country}_c)$ as controls.
Again, we add $Post_t \times country_c$ and $MP_j \times country_c$ as controls in $x_{jt}$, as well as country fixed effects $\gamma_c$, to properly isolate the merger’s effect on marginal costs. $\omega_{jt}$ is the error term.

Table 2 shows the results of our merger analysis based on the Bertrand model. In the first column, we constrain the effect to be equal across countries and infer an insignificant decrease in price. The second column confirms this finding, as none of the country specific effects turn out to be significantly different from zero.

The third and fourth column provide more insight in how the Bertrand model rationalizes these price evolutions. When only estimating a single cost efficiency over all countries, displayed in the third column, we infer a significant decrease in costs. The fourth column allows for differing cost efficiencies over countries and displays an interesting result suggesting that cost efficiencies differ greatly over countries. The largest cost efficiency is estimated at 14.4% in Italy versus an (insignificant) cost increase of 3.5% in the UK. This difference in cost efficiencies does not seem realistic and could be a result of using the Bertrand model, overestimating the market power effect in Italy compared to other countries. It could in fact be differences in conduct across countries that drive these results, wrongly attributed to cost efficiencies under the assumption of Bertrand competition. It seems likely that cost efficiencies are similar across countries, instead of the major differences we observe here, as they are most likely realized in the production process that is often common across observed markets. This is exactly what we investigate in the rest of this paper.

All control variables in table 2 have intuitive signs, in line with the literature, for all specifications.

4 Structural Model With Flexible Conduct

In order to investigate the role of conduct in a merger case, we construct a structural model of the European car market that allows us to calculate markups in both the pre- and post-merger periods. This enables us to decompose the price change in a change in markups predicted by the model and a change in marginal costs. Markups are expected to increase following a merger, while marginal costs could decline after a merger following efficiencies.

We construct an oligopoly model with multi-product firms who compete in prices, allowing for the possibility of coordinated behavior. Combined with a BLP (1995) random coefficient logit model, this enables us to predict firms’ markups following the merger.
4.1 Oligopoly model

Single conduct parameter

In order to predict markups based on prices and demand estimates, we have to make several assumptions about the form of competition that prevails in the market. We use a model similar to Nevo (2000a), extended to account for collusion as in Verboven (1996) and Goldberg and Verboven (2001). We assume that in a market $t$ with $F$ firms, the profit maximization problem of firm $f$ with portfolio $F_f$ is defined by

$$\Pi_f = \sum_{j \in F_f} (p_{jt} - mc_{jt}) s_{jt}(p_t) M + \phi \sum_{j \notin F_f} (p_{jt} - mc_{jt}) s_{jt}(p_t) M,$$

where $M$ is the market size, $s_{jt}(p)$ is market share as a function of prices and $mc_{jt}$ is the constant marginal cost of production. The first term on the right-hand side is firm $f$’s profit. $\phi$ is a conduct parameter on the unit interval that allows for the possibility that firms take the profits of their competitors into account. For $\phi = 0$, the model turns into a regular Bertrand-Nash model, while the value $\phi = 1$ implies a perfectly collusive market where all firms set prices as a profit maximizing cartel or a monopolist would. Note that this specification with one single conduct parameter implies that all firms treat each other the same way in their coordinating behavior. This is not necessarily a good representation of reality. Sudhir (2001) and Michel (2013) provide insight in cases where firms’ coordinating behavior varies over market segments or firms. Below, we will also allow for more flexible forms of conduct. It is possible to make assumptions about $\phi$, but the model also allows us to estimate it.

Assuming that in equilibrium firms compete Nash in prices, the profit maximizing price satisfies the following first order conditions for every product $j$ of firm $f$:

$$s_{jt}(p) + \sum_{r \in F_f} (p_{rt} - mc_{rt}) \frac{\partial s_{rt}(p_t)}{\partial p_{jt}} + \phi \sum_{r \notin F_f} (p_{rt} - mc_{rt}) \frac{\partial s_{rt}(p_t)}{\partial p_{jt}} = 0. \quad (7)$$

From this equation it is clear how a price change affects profits. First, a price increase of product $j$ increases profits given the current level of demand. Second, it lowers the demand for product $j$, thereby lowering profits. Lastly, it raises the demand for other products of firm $f$’s portfolio (and products of other firms it potentially coordinates with), mitigating the loss of demand for product $j$. 

10
These first order conditions can be written in vector notation, such that we get the following expression for backing out marginal costs:

\[ p_t - mc_t = -\Delta_t(\theta_d, \phi)^{-1}s_t(p_t) \Rightarrow mc_t = p_t + \Delta_t(\theta_d, \phi)^{-1}s_t(p_t). \]  

(8)

In this equation, \( \Delta_t \) is defined as follows,

\[ \Delta_t(\theta_d, \phi) = (H_t + \phi H^c_t) \odot \Omega_t, \]  

(9)

\( \odot \) denotes the Hadamard or element-wise product. \( H_t \) and \( H^c_t \) are matrices indicating ownership in market \( t \),

\[ H_{t,jr} = \begin{cases} 1, & \text{if } \exists f : \{j, r\} \subset F_f \\ 0, & \text{otherwise.} \end{cases}, \quad H^c_{t,jr} = \begin{cases} 0, & \text{if } \exists f : \{j, r\} \subset F_f \\ 1, & \text{otherwise.} \end{cases} \]

\( \Omega_{t,jr} = \partial s_{jt}(p_t)/\partial p_{jt} \) is a matrix of own and cross-price derivatives of market shares.

To estimate the conduct parameter, we need an assumption about the functional form of marginal costs. We logically revert to the specification we used under the Bertrand assumption in equation (6). Substituting this in (8), we can express price, \( p_t \), as a function of the data; demand, cost and conduct parameters; and the cost side error term.

\[ p_t = \exp(mc_t) - \Delta_t^{-1}(\theta_d, \phi)s_t. \]  

(10)

We take the log of this equation, as it is easier to interpret. The estimating equation then looks as follows:

\[ \log(p_t) = mc_t - \Delta_t^{-1}(\theta_d, \phi)\frac{s_t}{p_t}. \]  

(11)

**More flexible forms of conduct**

The model described above can easily be adapted to estimate more flexible forms of conduct. It is interesting to do so, since some of the differences in price effects of the mergers, might be explained by differences in conduct. Therefore, we can rewrite equation (9) as follows:

\[ \Delta_t = (H_t + \sum_c \phi_c H^c_t) \odot \Omega_t \]  

(12)

Here, we split up the complement of the holding matrix in multiple matrices. This way we can impose whatever structure we want on the way conduct conduct.

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4Detailed calculations are shown in the appendix.
differs between different firms. One way we define the complement of the holding matrix is that it consists of two parts, the products that are domestic to the market and the products that are not. In that case $H_t$ is the same as in the single conduct case but there would be two complement matrices:

$$
H_{t,jr}^{\text{dom}} = \begin{cases} 
1, & \text{if } \exists f : \{j, r\} \subset F_f, \{j, r\} \text{ are both domestic in market } t \\
0 & \text{otherwise.} 
\end{cases}
$$

$$
H_{t,jr}^{\text{non}} = \begin{cases} 
1, & \text{if } \exists f : \{j, r\} \subset F_f, \{j, r\} \text{ are both foreign in market } t \\
0 & \text{otherwise.} 
\end{cases}
$$

(13)

This way, both sets of products have their own conduct. This allows us to check whether domestic firms are more likely to cooperate, which would result in a higher $\phi$ among the domestic firms compared to non-domestic firms. There are numerous other ways to model conduct this way. Sudhir (2001) for instance, estimates different conduct parameters for each segment of the car market.

It is also possible to depart from using binary $H_t$ matrices. We can also include information about the firms that could be correlated to conduct. We can construct a matrix $m_{jk}$ where an entry in the $j$-th row and $k$-th column contains information about firm $j$ and $k$. When interacting this matrix with $H_t$ in equation (12), we can estimate a very flexible form of conduct that is very parsimonious in terms of the number of parameters that has to be estimated. An example of this approach is Ciliberto and Williams (2014), who construct a multi-market contact matrix.

Since multi-market contact is not relevant in our case - all firms enter all markets - we look for an alternative variable that is thought to influence on. Theoretically, anti-competitive pricing is more likely in concentrated markets among bigger companies. Therefore we construct a matrix, $sos_{t,jr}$, where an entry in the $j$-th row and $r$-th column indicates the sum of the market shares of both firms respectively owning products $j$ and $r$ in market $t$:

$$
sos_{t,jr} = \sum_{k \in F_j} s_k + \sum_{l \in F_r} s_l
$$

(14)

where $F_j$ and $F_r$ are the sets of products produced by the same firm that produces product $j$ and $r$ respectively.

We include this in our analysis with the following specification:

$$
\Delta_t = [H_t + \phi_1 H_t^c + \phi_2 (H_t^c \odot sos_t)] \odot \Omega_t.
$$

(15)

This basically allows for conduct that is specific for each pair firm, while only estimating one or two conduct parameters.
Actual conduct between any two firms producing \( j \) and \( r \) can then be calculated as \( \phi_{t,jr} = \phi_1 + \phi_2 \ast s_{t,jr} \). So \( \phi_1 \) basically acts as a general lower bound for conduct, while \( \phi_2 \) measures to what extent firms will collude more when their market shares get larger. For \( \phi_1 = 0 \) and \( \phi_2 \neq 0 \), conduct fully depends on market shares, while for \( \phi_1 \neq 0 \) and \( \phi_2 = 0 \) firms behave the same towards all competitors.

Note that these different definitions of \( \Delta_t \) have no impact on our expression for price, (11). It follows that the estimation procedure is the same for single or multiple conduct parameters.

### 4.2 Demand Estimation

To estimate demand we use a BLP (1995) random coefficient logit model closely following Nevo’s (2000b) notation. This model has the advantage that it can be estimated using market-level data, while producing more realistic substitution patterns than alternative discrete-choice models, such as the standard logit model.

Assume that a utility maximizing consumer \( i, i = 1,\ldots,I \), can choose between \( J \) car models, \( j = 1,\ldots,J \) in market \( t = 1,\ldots,T \). This consumer \( i \)’s utility can be written as

\[
 u_{ijt} = x_{jt} \beta_i - \alpha_i \left( \frac{p_{jt}}{y_t} \right) + \xi_{jt} + \epsilon_{ijt},
\]

where for model \( j \) in market \( t \), price is denoted by \( p_{jt} \), \( x_{jt} \) is a \( K \)-dimensional row vector of observable product characteristics, \( \xi_{jt} \) represents the characteristics unobservable to the econometrician, \( y_t \) is income, and \( \epsilon_{ijt} \) is a random variable distributed Type I Extreme Value. The coefficients \( \alpha_i \) and \( \beta_i \) are individual specific coefficients and can be modelled as \( \beta_{ik} = \beta_k + \sigma_k v_{ik} \), for characteristic \( k \), and \( \alpha_i = \alpha + \sigma_\alpha v_{i\alpha} \), where \( v_{ik} \) and \( v_{i\alpha} \) are random variables representing unobserved consumer heterogeneity.

Because a consumer might choose not to purchase one of the competing products in market \( t \), an outside good is required. Therefore, the utility from the outside good \( (j = 0) \) is defined as follows.

\[
 u_{i0t} = \xi_{0t} + \sigma_0 v_{i0} + \epsilon_{i0t}.
\]

Setting \( \xi_{0t} \) and \( \sigma_0 \) to zero, the utility of the outside good is normalized to zero, as is common in the literature.
We can decompose indirect utility as follows:

\[ u_{ijt} = \delta_{jt}(x_{jt}, p_{jt}, y_t, \xi_{jt}; \theta_1) + \mu_{ijt}(x_{jt}, p_{jt}, y_t, v_i; \theta_2) + \epsilon_{ijt} \]

\[ \delta_{jt} = x_{jt}\beta - \alpha \left( \frac{p_{jt}}{y_t} \right) + \xi_{jt}, \quad \mu_{ijt} = \left( \frac{p_{jt}}{y_t} \right) \sigma_\alpha v_i^\alpha + \sum_k x_{jt}^k \sigma_k v_i^k, \]  

(18)

where \( \theta_d = (\theta_1, \theta_2) \) is a vector containing all the demand parameters to be estimated. \( \theta_1 = (\alpha, \beta) \) enters linearly and \( \theta_2 = (\sigma_\alpha, \sigma_1, ..., \sigma_K) \) contains the nonlinear parameters. The first term, \( \delta_{jt} \), is a mean utility part, common to all consumers. The second term and third term, \( \mu_{ijt} + \epsilon_{ijt} \), represent a mean-zero deviation from mean utility, capturing consumer heterogeneity.

Consumers are assumed to purchase one unit of the good that gives the highest utility, or the outside good, implicitly defining the set of the consumer's attributes that lead to the choice of good \( j \), \( A_{jt} \):

\[ A_{jt}(x_t, p_t, y_t, \delta_t; \theta_2) = \{(v_i, \epsilon_{i0t}, ..., \epsilon_{iJt})|u_{ijt} \geq u_{ilt} \forall l = 0, 1, ..., J\} \]

(19)

Because this set defines the individuals who choose brand \( j \) in market \( t \), the market share of the \( j \)th product is an integral over the mass of consumers in the region \( A_{jt} \). Given that the distributions of \( \epsilon_{ijt} \) and \( v_i \) are independent, this integral is given by

\[ s_{jt}(x_t, p_t, y_t, \delta_t; \theta_2) = \int_{A_{jt}} dP^*_\epsilon(\epsilon) dP^*_v(v), \]

(20)

where \( P^*_.(.) \) denotes population distribution functions.

Assuming an extreme value distribution for \( \epsilon_{ijt} \), it is possible to approximate this integral by

\[ s_{jt}(x_t, p_t, y_t, \delta_t; \theta_2) \approx \frac{1}{ns} \sum_{i=1}^{ns} s_{jti} \]

\[ \approx \frac{1}{ns} \sum_{i=1}^{ns} \exp \left[ \delta_{jt} + \sum_{k=1}^{K} x_{jt}^k (\sigma_k v_i^k) \right], \]

(21)

where \( (v_1^i, ..., v^K_i), i = 1, ..., ns, \) are draws from \( P^*_v(v) \) and \( x_{jt}^k, k = 1, ..., K, \) are the variables with random slope coefficients.

The demand specification is completed by considering a demand equation that relates the vector of observed market shares in market \( t \), \( S_t \), with the market shares predicted by the model, \( (21) \), as seen in Berry (1994):

\[ s(\delta_t; \theta_2) = S_t. \]

(22)

Because the econometric error term, \( \xi_{jt} \), is likely to be correlated with price, and because it enters this equation in a nonlinear fashion, this equation will need to be transformed such that an instrumental variable method can be used.
5 Estimation and Identification

5.1 Conduct estimation

As mentioned before, we are able to estimate conduct. To do so, we follow a sequential approach, where the parameters determining demand are estimated independently of any behavioral assumption that is imposed on the supply side. Once the demand side is estimated, the supply side parameters can be estimated in a second stage.

By rewriting our supply side equation (11), $\omega$ can be written as a function of demand side and supply side parameters and the conduct parameter.

$$
\omega_t = p_t + \Delta_t^{-1}(\theta_d, \phi)s_t - \beta_{t,e}(post_t * MP) - \beta_2x_t - \beta_3trend_t - \gamma_t.
$$

Note that identification of conduct mainly comes from variation between markets, since $\phi$ is interacted with markups of all products within a market in the objective function. Further, market shares $s_t$ are endogenous on the cost side, since unobservable cost characteristics may influence the probability of consumers to purchase a specific car, and hence the market share of the car. An example of this could be advertising costs. Therefore we need to instrument for market shares.

Given that this is a sequential approach to estimating the supply side, the demand side parameters are treated as fixed. To estimate the conduct parameter, assume that $z$ is an exogenous matrix of instrumental variables that is correlated with market shares, but uncorrelated with $\omega$. Then, the conduct parameter and $\gamma$ can be estimated by minimizing the GMM-IV criterion.

$$
J(\phi) = \omega(\phi)'zWz'\omega(\phi)
$$

$W$ is the weighting matrix. The criterion is expressed solely in terms of $\phi$, because the linearly entering parameters can be obtained by two-stage least squares for any given value of $\phi$. These parameters can therefore be partialled out.

To instrument for market shares, which identify the conduct parameters, we use sums of characteristics of competing cars, as in BLP (1995). These are valid since characteristics of products competing with a product $j$ are likely to have an effect on the probability of consumers buying good $j$, and thus its market share, while they are unrelated to unobserved cost characteristics. Note that $sos_t$ is a function of market shares and thus also possibly endogenous. This is however also dealt with through the BLP instruments.

To minimize the criterion reliably and to compute accurate standard errors, the derivative of the error term with respect to $\phi$ is needed. To do so,
remember from equation 9 that $\Delta_t$ can be written as follows.

$$\Delta_t = (H_t + \phi H_t^c) \odot \Omega_t$$  \hspace{1cm} (25)

Following derivatives are then easy to calculate:

$$\frac{\partial \Delta_t}{\partial \phi} = H_t^c \odot \Omega_t,$$

$$\frac{\partial \Delta_t^{-1}}{\partial \phi} = -\Delta_t^{-1} \frac{\partial \Delta_t}{\partial \phi} \Delta_t^{-1} = -\Delta_t^{-1} (H_t^c \odot \Omega_t) \Delta_t^{-1},$$ \hspace{1cm} (26)

such that, the derivative of the unobserved cost shock with respect to $\phi$ is given as follows:

$$\frac{d\omega_t}{d\phi} = -\Delta_t^{-1} (H_t^c \odot \Omega_t) \Delta_t^{-1} s_t$$  \hspace{1cm} (27)

The derivative of the GMM criterion with respect to the non-linearly entering conduct parameter is then easy to compute.

$$\frac{dJ(\phi)}{d\phi} = 2 \left( \frac{d\omega_t}{d\phi} \right)^T z W z' \omega$$  \hspace{1cm} (28)

5.2 Demand

Following BLP (1995) we can invert the system in (22) to obtain $\delta$, such that we can calculate the structural demand error $\xi$.

$$\xi_{jt} = \delta_{jt} - (x_{jt}\beta - \alpha p_{jt})$$  \hspace{1cm} (29)

The demand side parameters, $\theta$, are then estimated using a GMM procedure as constructed by Nevo (2000b). Because price is likely to be correlated with the error term, we need a set of instruments, $Z = [z_1, ..., z_M]$, orthogonal to the error term:

$$E[Z_m \xi] = 0, \quad m = 1, ..., M.$$  \hspace{1cm} (30)

The parameters, $\theta$, can then be found in a minimization of the GMM objective function

$$\hat{\theta} = \arg\min_{\theta} \xi' Z \Phi^{-1} Z' \xi,$$  \hspace{1cm} (31)

where $\Phi$ is a consistent estimate of $E[Z' \xi \xi' Z]$. Note that the parameters $\theta_1$ enter this minimization problem linearly, while $\theta_2$ enters nonlinerly. This allows us to simplify the search by using the first order conditions with respect

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The derivative of the inverse of a matrix function is a result from matrix calculus, see for instance Dhrymes (2013).

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to $\theta_1$, to express $\theta_1$ as a function of $\theta_2$, as shown in the online appendix of Nevo (2000b). This enables us to limit the nonlinear search to the nonlinear parameters only.

As stated in equation (30), our estimation procedure depends on a set of exogenous instrumental variables, uncorrelated to the error term at the true values of the demand parameters. Therefore we start by assuming that product characteristics $x_{jt}$ are exogenous, such that they are instruments for themselves. This is a reasonable assumption since firms cannot quickly change the characteristics of the cars they produce. It is still necessary to find instruments for price because, assuming producers know the values of the unobserved product characteristics $\xi_{jt}$, prices are correlated with these unobserved characteristics. Therefore we use an approximation to Chamberlain’s optimal instruments (1987) as introduced by Berry, Levinsohn and Pakes (1999). Reynaert (2013) has shown that using these instruments, in favor of commonly used instruments such as polynomials of $x_{jt}$ or sums of characteristics of all other competitors, increases the estimator’s efficiency and stability.

Chamberlain’s (1987) optimal set of instruments for a single equation GMM, as given by Reynaert (2013), is:

$$g_{jt}(z_t) = E\left[\frac{\partial \xi_{jt}(\theta)}{\partial \theta'} | X_t \right], \quad (32)$$

where $X_t = x_{1t},...,x_{Jt}$ are the exogenous product characteristics.

The interpretation for the linear demand parameters, $\alpha$ and $\beta$, is straightforward:

$$E\left[\frac{\partial \xi_{jt}(\theta)}{\partial \beta'} | X_t \right] = E[x_{jt} | X_t] = x_{jt}$$

$$E\left[\frac{\partial \xi_{jt}(\theta)}{\partial \alpha} | X_t \right] = E[p_{jt} | X_t] = x_{jt}\gamma. \quad (33)$$

So the optimal instrument for $\beta$ is just $x_{jt}$, as we assumed above. The optimal instrument for $\alpha$ is the predicted price after regressing price on the exogenous characteristics $x_{jt}$, using the coefficients from this estimate, $\gamma$, to predict price. This is equivalent to the first stage of a two stage least squares estimation with price as the endogenous variable and the exogenous $x_{jt}$ as instruments. Note that these optimal instruments can be calculated without having to estimate the demand model in a first stage, as they do not depend on the demand parameters $\theta$.

The optimal instruments for the nonlinear parameters $\sigma$ are:

$$E\left[\frac{\partial \xi_{jt}(\theta)}{\partial \sigma'} | X_t \right] = E\left[\frac{\partial \delta_{jt}(s_{jt}, \sigma)}{\partial \sigma'} | X_t \right]. \quad (34)$$
Contrary to the optimal instruments of the linear parameters given in (33),
the expectation (34) is a function of the true demand parameters $\theta$. Therefore,
the optimal instruments for the nonlinear parameters cannot be computed directly from the data,
such that a first stage estimation of the demand model, with different, non-optimal instruments, is needed.

We follow Berry, Levinsohn and Pakes’ (1999) approximation to these
instruments, replacing the value of the derivatives in (34) by the derivatives
evaluated at the expected value of the unobservables $E[\xi_{jt}] = 0$. Their
procedure is as follows:

1. Obtain an initial estimate $\hat{\theta}$ with non-optimal instruments. We base
   this first estimate on the more traditional BLP instruments.

2. Compute the predicted price $\hat{p}_t = X_t \hat{\gamma}$

3. Use $\hat{\theta}$ to construct the predicted mean utility $\hat{\delta}_t \equiv X_t \hat{\beta} - \hat{\alpha} \hat{p}_t$, and then
   the predicted market shares $\hat{s}_t = s_t(\hat{\delta}_t, \sigma)$.

4. Compute the Jacobian of the inverted market share system $\delta_t(\hat{s}_t, \sigma)$
evaluated at $\hat{\sigma}$:

$$\frac{\partial \delta_t(\hat{s}_t, \sigma)}{\partial \sigma^*} \bigg|_{\sigma=\hat{\sigma}}$$

The Jacobian of the mean utility with respect to $\sigma$ is calculated as shown in
the online appendix of Nevo (2000b).

6 Findings

6.1 Demand Estimates

Table 3 displays the results for our demand estimation. The mean coef-
ficients, $\alpha$ and $\beta$, indicate how the average consumer values certain char-
acteristics. The random coefficients, $\sigma$, show to what extent consumers’
preferences are heterogeneous about those characteristics.

It is clear that consumers are price sensitive, from the positive and signif-
icate $\alpha$ coefficient. The extent to which consumers are price sensitive varies
though, as indicated by the significant random coefficient. A higher horse-
power over weight ratio is generally preferred by consumers, but the random
coefficient suggests that this is not the case for everyone, as it is large in size

Similar to Berry, Levinsohn and Pakes (1995), we use the exogenous characteristics,
sums of characteristics of all competing products and sums of characteristics of competing
products within the same firm as instruments
compared to the mean coefficient (0.657). The average consumer also dislikes cars with high fuel consumption, but again the random coefficient is large compared to the mean coefficient (-1.005 and 1.295 respectively), so some consumers do not experience it as negative. A large car is preferred by most, as the mean coefficient is high with a relatively low (but significant) random coefficient.

On average, consumers prefer lower cars and, more notable, cars that are produced by a domestic company. We did not estimate random coefficients for these variables, so we can not comment on the heterogeneity of these preferences.

Lastly the significant random coefficient for the constant indicates that consumer preferences for the outside good are heterogeneous among consumers.

Table 3: Demand estimates from the random coefficient logit model

<table>
<thead>
<tr>
<th>Coef.</th>
<th>St.Err.</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \alpha, \beta )</td>
<td></td>
</tr>
<tr>
<td>price/income (( \alpha ))</td>
<td>8.312</td>
</tr>
<tr>
<td>hp/weight</td>
<td>0.657</td>
</tr>
<tr>
<td>fuel</td>
<td>-1.005</td>
</tr>
<tr>
<td>width</td>
<td>12.740</td>
</tr>
<tr>
<td>height</td>
<td>-3.050</td>
</tr>
<tr>
<td>domestic</td>
<td>1.894</td>
</tr>
<tr>
<td>const</td>
<td>-14.634</td>
</tr>
<tr>
<td>( \sigma )</td>
<td></td>
</tr>
<tr>
<td>price/income</td>
<td>2.417</td>
</tr>
<tr>
<td>hp/weight</td>
<td>0.548</td>
</tr>
<tr>
<td>fuel</td>
<td>1.295</td>
</tr>
<tr>
<td>width</td>
<td>1.976</td>
</tr>
<tr>
<td>const</td>
<td>4.520</td>
</tr>
<tr>
<td>Hansen J-stat</td>
<td>1.36E-06</td>
</tr>
<tr>
<td>Own Elasticity</td>
<td>-10.309</td>
</tr>
<tr>
<td>Cross Elasticity</td>
<td>0.0718</td>
</tr>
</tbody>
</table>

Note: 12783 observations for the full sample 1970-1999. Results for the second stage of the estimation, using optimal instruments. Specification includes segment, brand and market fixed effects.
6.2 Conduct Estimation

Next we focus on the results of the conduct estimation. In this section we abstract from possible cost efficiencies and exclude the post-merger dummies. All tables in this section are based on the demand estimation displayed in Table 3.

Table 4 displays the results when only estimating a single conduct parameter over the entire sample, without including efficiencies. This yields no significant signs of conduct differing from Bertrand, since the conduct parameter, \( \phi \), is close to zero and statistically insignificant. Marginal costs increase when the ratio of horsepower over weight is increased as well as for wider cars. It is somewhat unexpected that cars that are less fuel efficient are more expensive to produce, but this is most likely due to the fact that more powerful cars are less fuel efficient, but also more expensive to produce. Lastly, whether or not a car is sold domestically does not seem to impact the marginal costs significantly.

Table 5 displays the results for multiple different specifications of conduct. All specifications include the same marginal cost characteristics as in table 4 as well as country fixed effects and a trend. The first panel repeats the result when modelling conduct as a single parameter. The second panel differentiates between conduct among firms operating in their domestic market and all other firm interactions. From this result, it appears that domestic firms do coordinate on prices. The conduct parameter for the non-domestic firms is insignificant and technically lies outside of the possible scope of conduct parameters. Therefore, we estimate conduct among domestic firms again, as-

<table>
<thead>
<tr>
<th></th>
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</tr>
</thead>
<tbody>
<tr>
<td>( \phi )</td>
<td>-0.253</td>
<td>0.392</td>
<td>0.159</td>
</tr>
<tr>
<td>log(hp/we)</td>
<td>0.742</td>
<td>0.017</td>
<td>0.881</td>
</tr>
<tr>
<td>log(width)</td>
<td>2.848</td>
<td>0.072</td>
<td>3.754</td>
</tr>
<tr>
<td>log(fuel)</td>
<td>0.997</td>
<td>0.019</td>
<td>0.644</td>
</tr>
<tr>
<td>domestic</td>
<td>0.005</td>
<td>0.010</td>
<td>-0.002</td>
</tr>
<tr>
<td>constant</td>
<td>-10.189</td>
<td>0.382</td>
<td>-13.509</td>
</tr>
<tr>
<td>country FE</td>
<td>Yes</td>
<td>Yes</td>
<td></td>
</tr>
<tr>
<td>trend</td>
<td>No</td>
<td>Yes</td>
<td></td>
</tr>
<tr>
<td>R2</td>
<td>0.668</td>
<td>0.684</td>
<td></td>
</tr>
</tbody>
</table>

Note: 12783 observations for the full sample 1970-1999. Results based on regression equation \( (11) \) and \( \Delta_t \) defined as in equation \( (9) \).
suming bertrand competition among non-domestic firms, in the third panel. This result confirms that domestic firms are likely to engage in price coordination as the conduct parameter is statistically different from zero. This might be explained by the fact that firms have higher market shares in their domestic market and have more contact with their domestic competitors. This is in line with the theory that both higher concentration and more interactions facilitate collusion. We tried estimating a specification where conduct is country specific. This proves problematic due to non-linearities in the objective function. Therefore we restrict the number of conduct parameters in the rest of the paper.

Table 5: Various forms of conduct

<table>
<thead>
<tr>
<th></th>
<th>Coef.</th>
<th>St.Err.</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\phi$</td>
<td>0.159</td>
<td>0.352</td>
</tr>
<tr>
<td>$\phi_{dom}$</td>
<td>0.412</td>
<td>0.215</td>
</tr>
<tr>
<td>$\phi_{nondom}$</td>
<td>-0.419</td>
<td>0.379</td>
</tr>
<tr>
<td>$\phi_{dom}$</td>
<td>0.457</td>
<td>0.186</td>
</tr>
<tr>
<td>$\varphi_1$</td>
<td>-0.048</td>
<td>0.319</td>
</tr>
<tr>
<td>$\varphi_2$</td>
<td>1.690</td>
<td>0.397</td>
</tr>
<tr>
<td>$\phi_{mean}$</td>
<td>0.274</td>
<td></td>
</tr>
<tr>
<td>$\phi_{min}$</td>
<td>-0.041</td>
<td></td>
</tr>
<tr>
<td>$\phi_{max}$</td>
<td>0.483</td>
<td></td>
</tr>
<tr>
<td>$\varphi_2$</td>
<td>1.321</td>
<td>0.244</td>
</tr>
<tr>
<td>$\phi_{mean}$</td>
<td>0.252</td>
<td></td>
</tr>
<tr>
<td>$\phi_{min}$</td>
<td>0.006</td>
<td></td>
</tr>
<tr>
<td>$\phi_{max}$</td>
<td>0.415</td>
<td></td>
</tr>
<tr>
<td>$\varphi_1$</td>
<td>-0.531</td>
<td>0.483</td>
</tr>
<tr>
<td>$\varphi_2$</td>
<td>0.316</td>
<td>0.080</td>
</tr>
<tr>
<td>$\phi_{mean}$</td>
<td>0.336</td>
<td></td>
</tr>
<tr>
<td>$\phi_{min}$</td>
<td>-0.215</td>
<td></td>
</tr>
<tr>
<td>$\phi_{max}$</td>
<td>0.733</td>
<td></td>
</tr>
</tbody>
</table>

Note: 12783 observations for the full sample 1970-1999. Results based on regression equation (11). $\Delta_t$ defined as in equation (12) for panels 1-3 and defined as in equation (15) for panels 4-6. Panel 5 sets $\phi_1 = 0$ and panel 6 replaces $sos_t$ with an ordinal variant (see footnote text). Same control variables and fixed effects for all specifications as in table 4.
One solution for estimating flexible patterns of conduct while having to estimate fewer variables, is by writing conduct as a function of other variables. Therefore, we write conduct as a function of $sos_t$ and estimate the model with $\Delta_t$ defined as in (15). The results of these estimates are displayed in panels 4-6 of table 5. The fourth panel displays the results for the base case, where conduct is defined as $\phi_{t,jr} = \phi_1 + \phi_2 * sos_{t,jr}$. The constant part of conduct is insignificant, in line with the results from table 4, but the positive and significant $\phi_2$ indicates that conduct increases when the sum of market shares between two firms increases. Since the slightly negative (but insignificant) $\phi_1$ leads to some firm combinations having a negative conduct parameter, we set $\phi = 0$. The results for this specification are in the fifth panel, confirming the findings in the first column. In the sixth panel, we replace the $sos_t$ variable with an ordinal version $sos_{ord}$ which would help address concerns of endogeneity of the $sos_t$ variable. The result is qualitatively very much in line with the first two columns, confirming the link between market power and conduct.

6.3 Marginal Cost Efficiencies

As mentioned before, it is possible to account for possible cost efficiencies generated by the merger by including the $post_t * MP_j$ interaction dummy in $x_t$ in equation 11. Table 6 revisits previous conduct estimations, but includes the merger efficiencies. We limit the sample to the data between 1979 and 1992 as to have a reasonable window to estimate the efficiencies related to the merger and prevent the effects of other mergers to spill into these results. Again, all specifications include the same cost characteristics as shown in table 4 as well as country fixed effects and a trend.

The first column repeats the conduct estimation without allowing for efficiencies, to see how the results change just by changing the sample, the second column introduces cost efficiencies. The first panel repeats the result of the difference-in-difference estimates in table 2 based on Bertrand conduct. Panels 2-6 respectively model conduct the same way as in the first five panels of table 5. Note from the first column that the single conduct parameter estimates are in line with our previous estimate, but the domestic conduct appears to be a bit higher compared to our full sample estimates. The coefficients in the $sos$ specifications are somewhat lower, but qualitatively similar to our previous estimates over the full sample length. In the second column, we see that accounting for conduct causes the estimated effi-

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8 $sos_{ord} = 1$ if $sos < 0.05$; $sos_{ord} = 2$ if $sos > 0.05$ & $sos < 0.15$; $sos_{ord} = 3$ if $sos > 0.15$ & $sos < 0.3$; $sos_{ord} = 4$ if $sos > 0.3$ & $sos < 0.5$; $sos_{ord} = 5$ if $sos > 0.5$. 

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Table 6: Various forms of conduct and merger efficiencies

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>( post_t * MP_j )</td>
<td>-0.056</td>
<td>0.018</td>
<td>-0.195</td>
<td>0.442</td>
<td></td>
</tr>
<tr>
<td>( \phi )</td>
<td>0.099</td>
<td>0.361</td>
<td>-0.449</td>
<td>0.345</td>
<td></td>
</tr>
<tr>
<td>( post_t * MP_j )</td>
<td>-0.047</td>
<td>0.017</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \phi_{dom} )</td>
<td>0.920</td>
<td>0.132</td>
<td>0.890</td>
<td>0.130</td>
<td></td>
</tr>
<tr>
<td>( \phi_{nondom} )</td>
<td>-0.253</td>
<td>0.348</td>
<td>-0.449</td>
<td>0.345</td>
<td></td>
</tr>
<tr>
<td>( post_t * MP_j )</td>
<td>-0.042</td>
<td>0.017</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \phi_{dom} )</td>
<td>0.993</td>
<td>0.083</td>
<td>1.008</td>
<td>0.076</td>
<td></td>
</tr>
<tr>
<td>( post_t * MP_j )</td>
<td>-0.040</td>
<td>0.016</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \phi_1 )</td>
<td>-0.290</td>
<td>0.467</td>
<td>-0.580</td>
<td>0.535</td>
<td></td>
</tr>
<tr>
<td>( \phi_2 )</td>
<td>0.989</td>
<td>0.629</td>
<td>1.719</td>
<td>0.756</td>
<td></td>
</tr>
<tr>
<td>( post_t * MP_j )</td>
<td>-0.041</td>
<td>0.017</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \phi_{mean} )</td>
<td>-0.205</td>
<td></td>
<td>-0.205</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \phi_{min} )</td>
<td>-0.575</td>
<td></td>
<td>-0.575</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \phi_{max} )</td>
<td>0.233</td>
<td></td>
<td>0.233</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( post_t * MP_j )</td>
<td>0.630</td>
<td>0.472</td>
<td>0.308</td>
<td>0.575</td>
<td></td>
</tr>
<tr>
<td>( \phi_{mean} )</td>
<td>0.104</td>
<td></td>
<td>0.051</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \phi_{min} )</td>
<td>0.009</td>
<td></td>
<td>0.005</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \phi_{max} )</td>
<td>0.194</td>
<td></td>
<td>0.095</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: 6118 observations for the sample 1979-1992. Panel 1 based on equation (1), panel 2-6 based on equation (11). \( \Delta_t \) defined as (12) for panel 2-4 and (15) for panel 5-6. \( \phi_1 = 0 \) in panel 6. Same control variables for all specifications as in table 4. Column 1 does not allow for cost efficiencies, column 2 does.

Cost efficiencies to decline, though only by about one standard error’s size. This is of course logical, since higher conduct before the merger means that the markup difference between pre- and post-merger period is smaller. Therefore, given observed prices, the difference in marginal costs before and after the merger is smaller.

Our last set of results, displayed in table 7, allows for the efficiencies to vary by country. Since our difference-in-difference estimates in table 2 show large differences in cost efficiencies based on a Bertrand assumption, which seems unlikely (especially since for instance costs do not seem to be lower for cars that are sold in the domestic market), we use this to check whether allowing for conduct yields more realistic patterns of cost efficiencies.
Table 7: Various forms of conduct and country specific merger efficiencies

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
</tr>
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<tr>
<td>$\phi_1$</td>
<td>-0.013</td>
<td>0.609</td>
<td>0.930</td>
<td>0.145</td>
<td>0.179</td>
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<tr>
<td>$\phi_2$</td>
<td>-0.228</td>
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<td>1.940</td>
<td>0.091</td>
<td>1.741</td>
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<tr>
<td>post<em>MP</em>BE</td>
<td>0.023</td>
<td>0.036</td>
<td>0.024</td>
<td>0.030</td>
<td>0.024</td>
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<td>-0.003</td>
<td>0.036</td>
<td>0.000</td>
<td>0.032</td>
<td>-0.007</td>
</tr>
<tr>
<td>post<em>MP</em>GER</td>
<td>-0.052</td>
<td>0.039</td>
<td>-0.044</td>
<td>0.034</td>
<td>-0.049</td>
</tr>
<tr>
<td>post<em>MP</em>IT</td>
<td>-0.144</td>
<td>0.035</td>
<td>-0.114</td>
<td>0.043</td>
<td>-0.083</td>
</tr>
<tr>
<td>post<em>MP</em>UK</td>
<td>0.035</td>
<td>0.038</td>
<td>0.041</td>
<td>0.033</td>
<td>0.042</td>
</tr>
<tr>
<td>$\phi_{mean}$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.321</td>
</tr>
<tr>
<td>$\phi_{min}$</td>
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<td>0.029</td>
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<tr>
<td>$\phi_{max}$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.598</td>
</tr>
</tbody>
</table>

Note: 6118 observations for the sample 1979-1992. Column 1 based on equation (1), Column 2-5 based on equation (11. $\Delta_t$ defined as (12) for column 2-3 and (15) for column 4-5. $\phi_1 = 0$ in column 5. Same control variables for all specifications as in table 4.

over countries. These results confirm that cost efficiencies following the merger are more uniform over countries. When assuming Bertrand, market share differences over countries predict artificially large changes in markup in countries where the merging parties already have a large market share. According to our results, firms are however already coordinating on prices more in markets where they have a large market share, thus violating the Bertrand assumption.

7 Conclusion

This paper provides different ways of modelling and estimating conduct and explores its role in ex post merger evaluation. We find some evidence for conduct departing from the Bertrand assumption. In particular when firms have higher market shares or operate in their domestic market, they seem to be be inclined to coordinate more. Therefore, the assumption of a Bertrand competition is violated and using it for merger evaluation can lead to biased results.

We study the merger between Fiat and Alfa Romeo and find that it did not lead to price increases. Upon observing prices before and after the merger, our model implies that the merger generated cost efficiencies which offset the markup effect of the merger, to explain the lack of price increase.

$^9$Better would be to estimate a conduct parameter for each country as well as country specific efficiencies. However, we noted before that estimating that many conduct parameters is very hard and results are unreliable. Our flexible specification where conduct is a function of the sum of market shares is a good second best option though, since in this specification conduct also varies by market because of the differences in market shares.
We argue that the differences in efficiencies over countries implied by the standard Bertrand model are somewhat unrealistic, due to the fact that it disregards differences in conduct, and show that modelling flexible forms of conduct helps to obtain more realistic estimates.
8 References


A Appendix: Aligning the demand and supply sides

We use different definitions of price on the demand and supply side. This note clarifies how to correct elasticities from the demand side and feed them into the supply side.

Demand

Remember equation (16) from the demand side.

\[ u_{ijt} = x_{jt} \beta_i - \alpha_i \left( \frac{p_{jt}}{y_t} \right) + \xi_{jt} + \epsilon_{ijt}. \]

Here, \( p_{jt} \) is expressed in local currency units and divided by income, \( y_t \). Setting \( \alpha_{it} = \frac{\alpha_i}{y_t} \), this can be expressed as

\[ u_{ijt} = x_{jt} \beta_i - \alpha_{it} p_{jt} + \xi_{jt} + \epsilon_{ijt}. \]

Given our demand model, this leads to the following derivatives of market shares with respect to nominal and real prices:

\[
\frac{\partial s_{jt}}{\partial p_{jt}} = - \frac{1}{nS} \sum_{i=1}^{nS} \alpha_{it} s_{ijt} (1 - s_{ijt}) = \frac{1}{y_t} \left( - \frac{1}{nS} \sum_{i=1}^{nS} \alpha_i s_{ijt} (1 - s_{ijt}) \right) = \frac{1}{y_t} \frac{\partial s_{jt}}{\partial \left( p_{jt}/y_t \right)}
\]

\[
\frac{\partial s_{jt}}{\partial p_{rt}} = \frac{1}{nS} \sum_{i=1}^{nS} \alpha_{it} s_{ijt} s_{irt} = \frac{1}{y_t} \left( \frac{1}{nS} \sum_{i=1}^{nS} \alpha_i s_{ijt} s_{irt} \right) = \frac{1}{y_t} \frac{\partial s_{jt}}{\partial \left( p_{rt}/y_t \right)}
\]

Supply

On the supply side, we use real prices in a common currency, SDR:

\[ p_{jt}^E = p_{jt} \times \left( \frac{e_{emt}}{CPI_t} \right). \]

Here, \( e_{emt} \) is the exchange rate between the common SDR currency and the currency in the local market, expressed in amount of SDR per unit of local currency. \( CPI_t \) is the consumer index in market \( t \).

Remember the profit maximization problem of firm \( f \) from equation (6).

\[ \Pi_f = \sum_{j \in F_f} (p_{jt}^E - mc_{jt}) \times M \times s_{jt}(p_t) + \phi \sum_{j \notin F_f} (p_{jt}^E - mc_{jt}) \times M \times s_{jt}(p_t) \]
Assuming the existence of a Bertrand-Nash equilibrium, the profit maximizing price satisfies the following first order conditions for every product $j$ of firm $f$:

$$s_{jt}(p_t) \frac{\partial p_E^{jt}}{\partial p_{jt}} + \sum_{r \in F_f} (p_r^{E} - mc_r) \frac{\partial s_{rt}(p_t)}{\partial p_{jt}} + \phi \sum_{r \notin F_f} (p_r^{E} - mc_r) \frac{\partial s_{rt}(p_t)}{\partial p_{jt}} = 0.$$ 

We substitute $\frac{\partial p_E^{jt}}{\partial p_{jt}}$ and account for the fact that we get $\frac{\partial s_{rt}(p_t)}{\partial (p_{jt}/y_t)}$ out of the demand side:

$$s_{jt}(p_t) \left( \frac{e_{emt}}{CPI_t} \right) + \sum_{r \in F_f} (p_r^{E} - mc_r) \left( \frac{1}{y_t} \right) \frac{\partial s_{rt}(p_t)}{\partial (p_{jt}/y_t)} + \phi \sum_{r \notin F_f} (p_r^{E} - mc_r) \left( \frac{1}{y_t} \right) \frac{\partial s_{rt}(p_t)}{\partial (p_{jt}/y_t)} = 0.$$ 

To rewrite this in vector notation, define the matrix $\Delta_t$ as follows.

$$\Delta_{t,jr}(\theta_d, \phi) = \begin{cases} \frac{\partial s_{rt}(p_t)}{\partial (p_{jt}/y_t)}, & \text{if } \exists f : \{r, j\} \subset F_f \\ \phi \left( \frac{\partial s_{rt}(p_t)}{\partial (p_{jt}/y_t)} \right), & \text{otherwise.} \end{cases}$$

This results in the following equation, which we can rewrite in multiple ways:

$$s_t(p_t) \left( \frac{e_{emt}}{CPI_t} \right) + \Delta_t(\theta_d, \phi) \left( \frac{1}{y_t} \right) (p_t^{E} - mc_t) = 0$$

$$p_t^{E} - mc_t = -y_t \Delta_t(\theta_d, \phi)^{-1} s_t(p_t) \left( \frac{e_{emt}}{CPI_t} \right)$$

$$mc_t = p_t^{E} + y_t \Delta_t(\theta_d, \phi)^{-1} s_t(p_t) \left( \frac{e_{emt}}{CPI_t} \right)$$

$$p_t^{E} = mc_t - y_t \Delta_t(\theta_d, \phi)^{-1} s_t(p_t) \left( \frac{e_{emt}}{CPI_t} \right).$$

If we make some assumptions about the functional form of marginal costs, we can estimate the $\phi$ parameters alongside the cost parameters. We experiment with a very basic log-linear cost specification, where log costs are explained by the characteristics of the car.

\[10\]Note that we implicitly assume that firms maximize profits in local currency units.
Log costs

\[ \log(mc_t) = \beta_1 c (post_t * MP_j) + \beta_2 x_{jt} + \beta_3 trend_t + \gamma_c + \omega_{jt} \]

Substituting marginal costs, we get our estimating equation

\[ p_t^E = \exp(mc_t) - y_t \Delta_t(\theta_d, \phi)^{-1} s_t(p_t) \left( \frac{e_{emt}}{CPI_t} \right). \]

For more straightforward interpretation, we take the log of this equation

\[ \log \left( p_t^E + y_t \Delta_t(\theta_d, \phi)^{-1} s_t(p_t) \left( \frac{e_{emt}}{CPI_t} \right) \right) = mc_t. \]

Which we can rewrite as

\[ \log \left( p_t^E \left( 1 + \frac{y_t \Delta_t(\theta_d, \phi)^{-1} s_t(p_t) \left( \frac{e_{emt}}{CPI_t} \right)}{p_t} \right) \right) = mc_t. \]

Given that \( \log(1 + \delta) \approx \delta \) for \( \delta \) close to 0, this simplifies to

\[ \log(p_t^E) - L = mc_t = \beta_1 c (post_t * MP_j) + \beta_2 x_{jt} + \beta_3 trend_t + \gamma_c + \omega_{jt}. \]

From this equation, we can recover the cost side error such that we can employ GMM to estimate cost and conduct parameters.