Pricing and Consumption Effects of Safety Regulation in the Automobile Industry

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Abstract

The imposition of product safety standards is a common practice amongst regulators (e.g. US Consumer Product Safety Commission). In an industry with differentiated products it affects firms to the extent that it increases costs and reduces firms’ ability to differentiate their products, which increases competition. This paper studies the pricing effects of a regulation that made safety equipment – Airbags and ABS – mandatory in Brazilian automobiles. By measuring the pricing effects of the regulation, we can assess which consumers are better off as a result of the regulation and to what extent they are better off. These distributional effects in conjunction with how much firms lose with the regulation are paramount to understand the lobbying forces in favor or against the policy.

**Keywords:** Safety regulation, Automobile Industry, Price Discrimination, Demand Estimation.

**JEL Classification:** L11, L51, L62
1 Introduction

“Cars Made in Brazil are Deadly.” - Associated Press, May 2013.

“Manufacturers and importers exert “enormous pressure” on regulators to avoid having to install additional safety features, says Alejandro Furas of Latin NCAP.” - The Economist, November 2015.

As the headline of the Associated Press article from 2013 and the Economist quotation point out very clearly, cars made in Brazil are unsafe and manufacturers are resistant about improving their safety standards. In fact, despite Airbags and Antilock Braking System (ABS) being old and effective technologies proven to reduce car occupants’ mortality rates\(^1\), they were offered as standard equipment in only 41% of the cars sold in Brazil in 2009.\(^2\) Since manufacturers incentives to offer Airbags and ABS do not stem directly from their social value but from the private returns manufacturers reap with them in the market place, it is safe to state that differentiating cars in terms of the presence of safety equipment is the most profitable action for the firms. Hence, understanding what are the market incentives faced by firms and how much they have to lose with safety requirement policies is the key to any policy targeting the improvement of automobile safety standards.

This paper studies the challenges faced by regulators when implementing product safety standards by empirically assessing the pricing and consumption effects of a specific regulation that made safety equipment – Airbags and ABS – mandatory in Brazilian automobiles. The mandate to add the safety equipment to every car generates two opposing forces affecting prices. First, there is an upward pressure due to the cost increase induced by the mandatory addition of safety equipment. Second, there is a downward pressure due to the intensified competition generated by the loss in the ability to differentiate the cars on the safety dimension. The net price response is an empirical matter and it is the key to understand what consumers benefit with the regulation (extensive margin) and how much they gain from it (intensive margin). Moreover, it also measures how much firms lose with the regulation and hence it provides a ballpark of their lobbying incentives.

The Brazilian automobile industry is the ideal place to study the empirical challenges associated with the implementation of mandatory safety standards. First, the regulation established a transition period from 2010 to 2012 in which manufacturers were required to gradually increase the supply of cars sold with safety equipment.\(^3\) The gradualism in the adoption of safety equipment by manufacturers generates variation in the competitive environment faced by cars with safety

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\(^{1}\)National Highway Traffic Safety Administration (NHTSA).

\(^{2}\)Own calculation based on data from “Quatro-Rodas” which is a magazine specialized in cars.

\(^{3}\)In fact, the transition period was from 2012 to 2013 but we only have data up to 2012.
equipment. Furthermore, the Brazilian automobile industry has a well-organized association of manufacturers (Anfavea) and is one of the largest and most concentrated market in the world (Cosar et al., 2015). Therefore, if required, firms have the incentives and the capability to lobby against policies that might reduce their profits.

Our point of departure is Bresnahan et al. (1997) observations that (i) markets for differentiated products often exhibit some form of segmentation according to the presence of specific product attributes (“principles of differentiation” or simply PD in their nomenclature); and (ii) good candidates to be PDs are attributes that cannot be added to a car in the secondary market. The idea behind this argument is that if there is a competitive secondary market for an attribute, then consumers will equalize their marginal valuation for the attribute to the price in the secondary market and hence there will be no ex-post heterogeneity. These observations together with the fact that a car (e.g. Honda Civic) is offered in many different versions (e.g. Honda Civic LX, Honda Civic LXS, Honda Civic EX) that share common design/style components that cannot be affected by consumers motivate the first PD used in the paper – the car model. The second PD considered in the paper is defined to be the presence or not of safety equipment (Airbag and ABS). Differently than other car attributes, technical restrictions make virtually impossible to add safety equipment to a car.

With detailed data on car registration, attributes and prices at the model/trim level, for the period that goes from 2005 to 2012 I document the importance of the car model and safety as market segmentation variables. The descriptive analysis of the data indicates that cars with safety equipment are systematically more expensive than the ones without safety equipment. This difference occurs when we compare cars of different models, when we compare different trims (versions) of the same model and it is robust to controlling for other car attributes. Of course, these results are not surprising at all. However, an interesting pattern arises when we compare the impact of safety equipment on the price of a car before the regulation was enacted (2005 to 2009) with the impact of safety equipment on the price of a car during the transition period imposed by the regulation (2010 to 2012). This comparison is done by estimating separate hedonic regressions in each sample and indicate a drop of R$ 5574 in the implicit price for safety.4

There are many factors that could rationalize the stark drop in the implicit price for safety during the transition period imposed by the regulation. Chief among them are: (i) a reduction in the effect of safety on marginal cost; (ii) the increased competition on the safety dimension.

4Specifically, the clustering variable used throughout the paper is a dummy variable that is 1 if the car has abs or airbag and 0 otherwise.
5As an example, consider the case of the Honda Civic. Civic is the models and the possible trims are LX, LXS and EX. Hence, the data provides detailed information for the Honda Civic LX, Honda Civic LXS and Honda Civic EX.
6All of the monetary variables in this paper are in Brazilian currency of 2010 (reais - R$). To have an idea of how much a value would be in dollars one should divide by 3.
induced by the fact that during this period there is an increase in the number of cars with safety equipment; and/or (iii) a change in firms’ ability to perform second-degree price discrimination by offering trims of the same model with or without safety equipment. To measure the role of safety on marginal costs I estimate a structural model of supply and demand for automobiles using the framework developed by Berry et al. (1995) and extended by Goldberg and Verboven (2001); Grigolon and Verboven (2014); Grigolon et al. (2017). The demand model accommodates the principles of differentiation (car model and presence of safety) by assuming a two-level nested logit structure. Moreover, the model is flexible enough to capture consumer heterogeneity in their price sensitivity coefficient. With the demand estimates at hand and assuming that firms play a Bertrand-Nash game we recover the impact of safety and other attributes in the marginal cost of a car.

The demand estimates reveal a large degree in consumers’ price sensitivity and they also imply that car model and presence of safety are relevant segmentation dimensions; the nesting parameter estimates satisfy the random utility maximization restrictions and are significant. The pricing equation estimates indicate that during the transition period defined by the regulation, the effect of safety on marginal costs decreased from R$ 6700 to R$ 1300 while the markup on safety (levels) decreased from R$ 500 to R$ 200. These estimates point out a surprisingly large reduction in the marginal cost of safety but they are not helpful in suggesting what are the possible competitive effects of the regulation. First, we are making a before and after analysis and thus there are many factors that we are not able to control that might affect the results. Second, this analysis just states that markups in levels are decreasing but do not explain what is causing this fall; is it generated by a competitive effect caused by an increase in the number of cars that have safety equipment? Or is it because the regulation changes the ability of firms to induce price discrimination within a model (second-degree price discrimination)? To overcome these issues, the next step of the paper is to use the supply and demand estimates to run a counter-factual exercise that would allow me to disentangle both effects. The exercise I have in mind considers a market with $N$ car models such that each model has two versions/trims ($2^N$ observations). The first counter-factual computes the equilibrium prices assuming that every model has one version with safety equipment and another version without safety equipment. Moreover, the second counter-factual computes the equilibrium prices assuming that both versions of every model have safety equipment. Comparing the within model markup difference across both counter-factual worlds provide a measure of how important is the second-degree price discrimination. Furthermore, comparing how the average markup on safety varies across each counter-factual will provide us a measure of the competitive effect.

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7In percentage the markup on safety increased from 7% before the regulation to 23% during the transition period.  
8One possible explanation for this large cost reduction is that by adding safety equipment to more cars firms obtain gains of scale.
The contributions of this paper are twofold. First, by studying the market incentives that manufacturers have to offer safety equipment in their cars and the distributional effects of mandatory safety equipment regulation, this paper contributes to the policy debate regarding automobile safety that is currently taking place in developing countries. Second, this paper contributes to a large literature on estimating supply and demand for the automobile industry Berry et al. (1995, 1999); Petrin (2002); Cosar et al. (2015); Barwick et al. (2016). In modeling demand, the main concern of these papers has been to take into account the differentiation across car models in the market. However, by doing so they ignore an important feature of the market which is that a car model is usually offered in many different versions. A few attempts have been made to overcome this issue but they usually impose additional restrictions; e.g Verboven (2002) models’ version choice (diesel or gasoline) conditional on choosing a specific car model and Grigolon et al. (2017) assumes that with the exception of a common unobserved term the preferences for different versions of the same car model are independent (no PD in the car model dimension). Our novelty lies in recognizing that the taste for different versions of the same car model might be correlated and hence we can use the principle of differentiation idea to model demand.

2 Industry Description and Data

2.1 Institutional Background

Ralph Nader’s book “Unsafe at any speed”, released in 1965, ignited the public debate regarding automobile safety in the US. In light of the high death rates of car occupants in Brazil and the low safety ratings of the Brazilian cars, one may say that Nader’s book title is also a precise description of the cars sold in Brazil in recent years. Targeting the improvement of automobile safety standards, the Brazilian government enacted the Safety Acts 311 and 312 in March 2009. The Safety Acts 311 and 312 defined the conditions under which firms should add Airbags and ABS, respectively, to the new cars produced. They established that starting in 2010, 8% of the new cars produced by each firm would have Airbags and ABS. This share would increase to 15% in 2011, 30% in 2012, 60% in 2013 and finally, 100% in 2014. Furthermore, during the transition period firms did not necessarily need to add Airbag and ABS to the same car, what matters was just the share of total production that had the respective safety feature.

During the transition period defined by the safety acts, it was not clear if the government would stick to the original deadlines or would postpone them at some point. An evidence supporting this claim is the resistance of some firms, specially Fiat and Volkswagen and of unions of worker against...
the safety acts. This resistance reached a point such that in December of 2013 the Minister of the Economy decided to edit the safety acts in order to postpone the deadline. However, some politicians and consumer groups backlashed and thus the Minister changed his mind and maintained the original deadline.\textsuperscript{11}

It should be pointed out that firms resistance against the regulation is not unwarranted. First, the regulation is detrimental to firms in two aspects: (i) the mandate to add Airbags and ABS to every automobile raises firms costs; and (ii) by adding the safety equipment to every car firms lose one dimension in which they can differentiate their vehicles. The reduced differentiation increases competition and thus should have a negative effect on prices. Second, the Brazilian automobile market is responsible for 5\% of the Brazilian GDP, it was the forth largest market in the world in 2010 and it is one of the most concentrated and closed to imports (Cosar et al., 2015) and hence the stakes for firms are large. The potential for big losses in conjunction with the presence of a well organized manufacturing association (Anfavea) gives firms the capabilities to lobby against policies that goes against their interests.

2.2 Data

Estimating a differentiated product-level supply and demand system for the Brazilian automobile market requires data on prices, quantities and characteristics of each car sold in each year considered in the paper. In addition, it also requires a measure of market size. The dataset gathered comprises vehicles manufactured in Brazil, Mercosur or Mexico for the period of 2005 to 2012, with the exception of SUVs and trucks. An observation consists of a vehicle, at the model/trim/displacement level.

The data were assembled using three main sources: (i) The national department of traffic (DENATRAN in the Portuguese acronym); (ii) Quatro Rodas which is a magazine specialized in automobiles; and (iii) the National Bureau of Statistics (IBGE in the Portuguese acronym).

Quantities were obtained from a dataset provided by DENATRAN and covers the years from 2005 to 2012. In Brazil, one is required to pay a fee when registering a new car and also to pay a yearly ownership tax that depends on the market value of the car. Hence, we would expect the government to keep an accurate record of the number of new vehicles registered. For most cars in the DENATRAN data, the information available is of quantity registered, in a given year, at the model/trim/displacement level. When this level of information is not present, I have quantity registered at the model/trim level. The market size variable was obtained from IBGE.

\textsuperscript{11}The discussion around this controversy can be seen on the following websites: http://revistaautoesporte.globo.com/Noticias/noticia/2013/12/lei-que-obriga-airbag-e-abs-em-carros-novos-partir-do-proximo-ano-podera-ser-adiada.html . The late government note sticking with the original deadlines can be seen here: http://www.brasil.gov.br/economia-e-emprego/2014/01/carros-fabricados-no-brasil-devem-ter-airbags-e-freios-abs
and it is constructed as the number of households that are included in the middle class and above, i.e., households with monthly income equal to or greater than 3 minimum wages. Price and characteristics data were collected from Quatro Rodas which provides detailed information at the model/trim/displacement for every vehicle manufactured in Brazil, Mercosur or Mexico. This information includes price, horsepower and if safety and comfort features like abs, airbag, air-conditioning and power steering wheel are standard, optional (add-on) or not available.

The matching between the quantity data and characteristics data was made according to the following rule: Whenever possible, which is the case for most observations, there is a one to one match at the model/trim/displacement level. For the rare cases in which the quantity data is available only at the model/trim level, the quantity was assigned to the model/trim with smallest displacement. Not surprisingly, the observations with quantity information only at the model/trim level are of smaller and cheaper cars.\textsuperscript{12} Fortunately, this should not be a big issue because in all of these cases, there is no difference in the availability of safety and comfort features across trims with different displacements. In order to ease the notation, from now on, I will omit the displacement part and call an observation model/trim.

Our final sample is an unbalanced panel that covers 87\% of all car registrations in Brazil, excluding SUVs and trucks, in the period from 2005 to 2012. Table (1) displays the coverage for each year. The clear downward trend in the coverage of the sample relative to all cars registered can be explained by two main factors: (i) the entry of Korean and Chinese brands that at the time did not have plants in Brazil, Mercosur or Mexico; and (ii) the shift in demand towards SUVs.\textsuperscript{13} Moreover, once you consider that the Mercosur countries and Mexico were not big exporters to Brazil in this period (Anfavea, 2016), then table (1) indicates how closed the Brazilian market is.

\begin{table}[h]
\centering
\caption{Sample coverage - (\%) of total sales}
\begin{tabular}{ll}
\hline
Year & Coverage(\%) \\
\hline
2005 & 92.61 \\
2006 & 91.39 \\
2007 & 89.50 \\
2008 & 93.69 \\
2009 & 86.35 \\
2010 & 84.38 \\
2011 & 82.10 \\
2012 & 83.15 \\
\hline
Total & 87.03 \\
\hline
\end{tabular}
\end{table}

The key variable in this paper is the one that captures if safety features are standard equipment in the model/trim. To construct such variable, I use an indicator that is equal to one if the

\textsuperscript{12}Celta and Corsa Hatch/Sedan in 2005; Celta, Corsa Hatch/Sedan, Palio ELX and Siena ELX in 2006 and 2007; Corsa Hatch Maxx, Palio ELX and Siena ELX in 2008 and 2009.

\textsuperscript{13}This shift in demand towards SUVs resulted in the Honda HR-V, which is a small SUV, to be one of the best sellers in Brazil in 2010 and 2017.
model/trim has airbag and/or abs as a standard feature and zero if both are optional (add-on), not available or a combination of optional and not available. Furthermore, the variables that capture the presence of the comfort features air-conditioning, power steering wheel and automatic transmission are constructed in an analogous way. These dummy variables are labeled AIR, PWRWHEEL and AT.

Different than other papers about the automobile industry, I am able to match quantities and characteristics at model/trim level and not just assign the features of the base trim, or some other average measure of characteristics, to quantities (Berry et al., 1995, 1999; Petrin, 2002; Cosar et al., 2015). This feature of my data makes it less likely that the safety features will capture other non-observables as it would be the case if the data were constructed following the previous literature. Despite this advantage of my data, there is still a source of concern that must be addressed: the fact that some model/trims have safety features as optionals and consumers might be purchasing them as add-ons. Specifically, if transitions in model/trim safety status (do not have safety to have safety) come disproportionally from model/trims that have it as optional and consumers were already buying these model/trims with safety add-ons, then we should not expect any variation is substitution patterns among model/trims with safety. Therefore, if we observe such variation in the data, it is likely to be due to measurement error and/or changes in unobservables.

Since I do not observe add-on choice, I can not address this issue directly. However, I can still use industry information to argue that safety features are not a common choice of add-ons and therefore the variation in the data is not due to measurement error or unobservables. The first argument is a revealed preference one; if consumers were purchasing the safety equipment as add-ons to their cars, then the regulation would not be required in the first place. The second argument relies on anecdotal evidence about the industry; manufacturers tend to price the add-on safety features in a way to provide incentives to the consumers to buy a model/trim that already has it as standard instead of adding it to the trim. The common strategies to do so are: (i) to sell the safety features bundled with other features and as a consequence substantially increasing the price of acquiring it as add-on; and (ii) to take long periods of time (e.g. a month) to deliver cars that have to be manufactured with add-ons.

Last but not least, I can empirically test if model/trims that have safety features as optional add-ons in period $t$ are more likely to have it as standard features in period $t + 1$. If this is not the case, then the previous issue is of diminished importance. The estimates of the linear probability model used to test the aforementioned hypothesis are displayed in table 2. The base group are the model/trims in which safety features are not available at $t$. The coefficient on $\text{OptionalSafety}_t$ measures how different is the probability of having a safety feature in $t + 1$ given that safety was 

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14 A report from Cesvi states that the addition of Abs to a car generates an increase in the price of the vehicle that ranges between 5% to 44%.
optional in \( t \). As we can see there is no significant difference between both groups. Furthermore, the coefficient on the interaction between \( \text{OptionalSafety}_t \) and a dummy variable that is one after the regulation was enacted and zero before will measure if the law changed the safety feature adoption behavior. Again, we do not observe any statistical difference between groups. As these results provide evidence that there is no systematic difference in the adoption of safety features between model/trims that have it optional or not available, they are reassuring about the quality and measurement of the key variable safety.

Table 2: Estimates of the probability of safety adoption.

<table>
<thead>
<tr>
<th>Dependent Variable</th>
<th>( \text{StandardSafety}_{t+1} )</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
</tr>
<tr>
<td>( \text{OptionalSafety}_t )</td>
<td>0.0191</td>
</tr>
<tr>
<td></td>
<td>(0.0189)</td>
</tr>
<tr>
<td>( \text{OptionalSafety}_t \times \text{After}_t )</td>
<td>-0.0268</td>
</tr>
<tr>
<td></td>
<td>(0.0434)</td>
</tr>
<tr>
<td>Constant</td>
<td>-0.428</td>
</tr>
<tr>
<td></td>
<td>(0.507)</td>
</tr>
</tbody>
</table>

Observations 676 675 676  
R-squared 0.073 0.102 0.241  
Year FE Yes Yes Yes  
Maker FE No Yes No  
Body FE No Yes No  
Model FE No No Yes  

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Tables 3 through 5 display a portrait of the automobiles demanded in Brazil during the years under study. Table 3 highlights the importance of safety features in generating market segmentation between different models and within a model. First, note that despite the steady increase in the number of models available (column 1), the average number of trims per model is relatively constant around three during all periods of time in the sample (column 2). One interpretation for this pattern is that car models provide some insulation from competition and thus the increase in the number of models available do not substantially affect firms incentives to induce price discrimination within a model. The evolution of the segmentation between models in terms of their safety status can be seen from column 3.

As expected, before the regulation most models did not have even a trim with standard safety. However, the number of models that have at least one trim with standard safety features grows considerably after the regulation takes place. The information in columns 4 through 8 is useful to understand the role of safety features as a within model differentiation tool. From column 4, note that there is a reasonable price difference within a car model based on the trim safety status and this difference falls sharply after the enactment of the regulation. One possible explanation for this
observed behavior is that by forcing firms to offer safety features in every model/trim, the law was able to reduce within model discrimination and thus price dispersion. Finally, columns 5 through 8 display the count of the number of models according to their share that have standard safety features. As expected, there is variation in the safety status within a trim and the enactment of the law generated a reduction in this variation.

Table 3: Variation of trims within a model

<table>
<thead>
<tr>
<th>Year</th>
<th>#Models</th>
<th>Avg. #trims</th>
<th># Models with safety</th>
<th>∆P (0, 25%)</th>
<th>(0, 25%)</th>
<th>[25%, 50%)</th>
<th>[50%, 75%)</th>
<th>[75%, 100%]</th>
</tr>
</thead>
<tbody>
<tr>
<td>2005</td>
<td>49</td>
<td>3.27</td>
<td>24</td>
<td>17.35</td>
<td>1</td>
<td>4</td>
<td>7</td>
<td>12</td>
</tr>
<tr>
<td>2006</td>
<td>52</td>
<td>3.19</td>
<td>25</td>
<td>16.04</td>
<td>1</td>
<td>7</td>
<td>4</td>
<td>13</td>
</tr>
<tr>
<td>2007</td>
<td>54</td>
<td>3</td>
<td>27</td>
<td>13.48</td>
<td>1</td>
<td>5</td>
<td>2</td>
<td>19</td>
</tr>
<tr>
<td>2008</td>
<td>59</td>
<td>2.97</td>
<td>32</td>
<td>14.07</td>
<td>1</td>
<td>5</td>
<td>3</td>
<td>23</td>
</tr>
<tr>
<td>2009</td>
<td>66</td>
<td>2.98</td>
<td>34</td>
<td>9.86</td>
<td>0</td>
<td>3</td>
<td>2</td>
<td>29</td>
</tr>
<tr>
<td>2010</td>
<td>66</td>
<td>3.36</td>
<td>38</td>
<td>4.94</td>
<td>1</td>
<td>6</td>
<td>1</td>
<td>30</td>
</tr>
<tr>
<td>2011</td>
<td>71</td>
<td>3.18</td>
<td>47</td>
<td>5.25</td>
<td>0</td>
<td>6</td>
<td>7</td>
<td>34</td>
</tr>
<tr>
<td>2012</td>
<td>73</td>
<td>3.03</td>
<td>52</td>
<td>6.19</td>
<td>1</td>
<td>2</td>
<td>9</td>
<td>40</td>
</tr>
</tbody>
</table>

Notes: “# Models with safety” measures the number of models that have at least one trim with safety features being offered as a standard equipment. ∆P is the average across models of the within model price difference based on safety status of the trims (in 1000’s of reais). “Count # models” presents the number of models according to the share of their trims that have safety equipment.

To continue the analysis of the role of safety feature as a segmentation tool, I ran hedonic regressions. The standard interpretation for the coefficients of the hedonic regression is that they capture the cost of the attribute and also how the attribute affects markups. Hence, estimating the hedonic regression before and after the regulation will shed light on the cost and demand factors associated with vehicle characteristics and how they have evolved over time.

Table 4 displays the results of the hedonic models in two different samples. The first sample is restricted only to the years prior to the regulation (2005 through 2009). The second sample is restricted to the years after the regulation was enacted (2010 through 2012). The odd columns have maker and body type fixed effects. The even columns have model fixed effects. As we can see, the implicit prices for the safety features were the ones that faced the highest drop. Comfort features like automatic transmission and air conditioning also faced a significant reduction on its implicit price but not as much as safety features. Moreover, the implicit prices for power steering wheel and displacement do not seem to have changed much in the two different periods. Note that the patterns observed in the data relative to the safety features are consistent with a cost and/or a markup reduction. However, it is unlikely that cost reductions are the main source. The point is that safety features are well established in the industry and have been offered for decades; it is unlikely that the industry faced a main technological shock or large gains of scale in this period. As a consequence, it is safe to conclude that after the enactment of the regulation there was a reduction in markups associated with safety features, which is consistent with the story that they

15To see why this is the case, think about the pricing equation derived from firms FOC. According to this equation, price is marginal costs plus markups. Assuming that marginal costs are a function of vehicle attributes and considering that markups are a function of the same attributes and also demand factors, we will have that a regression of price on these product attributes will generate coefficients that capture cost and demand factors.
play an important role in generating differentiation.

Table 4: Hedonic regression

<table>
<thead>
<tr>
<th>Dependent Variable</th>
<th>2005-2009 Price</th>
<th>2010-2012 Price</th>
</tr>
</thead>
<tbody>
<tr>
<td>SAFETY</td>
<td>7563.99</td>
<td>4297.46</td>
</tr>
<tr>
<td>AIR</td>
<td>6621.06</td>
<td>3504.3</td>
</tr>
<tr>
<td>AT</td>
<td>6654.64</td>
<td>4027.27</td>
</tr>
<tr>
<td>PWRTRWHEEL</td>
<td>2175.76</td>
<td>896.16</td>
</tr>
<tr>
<td>DISPLACEMENT</td>
<td>13371.53</td>
<td>14230.39</td>
</tr>
</tbody>
</table>

| Observations | 860 | 860 | 666 | 666 |
| R-squared    | 0.84| 0.92| 0.82| 0.92|
| Year FE      | Yes | Yes | Yes | Yes |
| Maker FE     | Yes | No  | Yes | No  |
| Body FE      | Yes | No  | Yes | No  |
| Model FE     | No  | Yes | No  | Yes |

Note: Robust standard errors in parentheses.

Finally, I split the data according to the presence or lack of safety features. Table 5 display the evolution of the average car demanded, without safety (Panel A) and with safety (Panel B). The most striking feature of this table is that despite the difference in trends between groups, their shares do not fluctuate much over time before the enactment of the regulation. The demand for cars without safety features has been moving slowly towards more comfortable and powerful cars. As expected, given that features are not changing much, prices are relatively constant over time with the exception of the drop in 2009. This drop can be mainly attributed to a tax cut imposed by the government in 2009. On the other hand, when we look for cars that have safety features, we can clearly see that they move towards more comfortable, larger and powerful cars. Note also that these movements tend to be associated with price increases. Furthermore, it is clear that the regulation changed the composition of both groups of cars. All in all, it seems like the set of variables used here is doing a good job in controlling for relevant factors and unobservables are probably not a key factor driving the shares in each group.

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16 As a policy to stimulate the Brazilian market in the face of the world financial crises, the government reduced taxes of all vehicles. The vehicles most affected by the tax cuts were the ones with engine displacement of 1L, which had their tax rate reduced to 0.
Table 5: Characteristics of the cars sold by safety status.

Panel A: Characteristics of the cars sold with no safety features.

<table>
<thead>
<tr>
<th>Year</th>
<th>obs.</th>
<th>sales</th>
<th>share</th>
<th>price</th>
<th>air</th>
<th>pwrwheel</th>
<th>displacement</th>
<th>hp</th>
</tr>
</thead>
<tbody>
<tr>
<td>2006</td>
<td>106</td>
<td>1282543</td>
<td>85.944</td>
<td>.16</td>
<td>.31</td>
<td>1.21</td>
<td>78.99</td>
<td></td>
</tr>
<tr>
<td>2007</td>
<td>95</td>
<td>1597155</td>
<td>87.101</td>
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Panel B: Characteristics of the cars sold with safety features.

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<th>sales</th>
<th>share</th>
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Notes: Except for sales and share, the entry in each column is the sales weighted mean. Prices are in thousands of 2010 R$.

3 An Equilibrium Oligopoly Model of the Brazilian Automobile Industry

This section presents the behavioral model. The model is composed of firms and consumers. Firms (e.g. Honda) produce cars. A car is defined as the pair model (e.g Honda Civic), trim (e.g Honda Civic LX or Honda Civic EX) and it is modeled as a bundle of attributes. Trims of the same model might differ in the availability of comfort features, safety features and engine power but have a common unobserved (to the Econometrician) attribute, e.g style. Consumers observe prices and choose among one of the cars offered or the outside option of not buying a new car. The next subsection defines how consumers make choices. The last subsection presents the supply model.

Demand

A car $j$ is defined as a model/trim pair (e.g Honda Civic EX, Honda Civic LX) and as it is standard in the literature it is modeled as a bundle of attributes. The key differences relative to other papers Berry et al. (1995); Verboven (2002); Grigolon et al. (2017) are twofold: (i) cars that belong to the same model (e.g Honda Civic EX, Honda Civic LX) are allowed to have common characteristics and (ii) consumer unobserved heterogeneity for each car is allowed to be correlated among trims.
of the same model.

The conditional indirect utility of a car $j$ for consumer $i$ in year $t$ depends on the price and characteristics of the car:

$$u_{ijt} = x_{jt} \beta - \alpha_i p_{jt} + \tilde{\xi}_{jt} + \epsilon_{ijt}$$

$$i = 1, \ldots, I; \quad j = 0, \ldots, J; \quad t = 2005, \ldots, 2012$$

(1)

The set of characteristics of the car $j$ includes a $K$-dimensional vector of observed characteristics, $x_{jt}$, a scalar characteristic which is observed by consumers and firms but not to the Econometrician, $\tilde{\xi}_{jt}$, and an idiosyncratic term that captures the unobserved taste of consumer $i$ for car $j$, $\epsilon_{ijt}$.

First, let’s start with the specification of the scalar unobserved characteristic $\tilde{\xi}_{jt}$. Define $m$ to be a subscript indexing the car model (e.g. Honda Civic, Toyota Corolla, VW Jetta, etc). Moreover, assume that $\tilde{\xi}_{jt}$ is additive in two terms:

$$\tilde{\xi}_{jt} = \xi_m + \xi_{jt}$$

(2)

where $\xi_m$ captures the unobserved characteristics that are common among all trims of the same model (e.g. prestige, style or advertising) and $\xi_{jt}$ captures shocks that are model/trim specific.

Following the literature, we can decompose the conditional indirect utility $u_{ijt}$ in two parts. Let,

$$\delta_{jt} = x_{jt} \beta + \xi_m + \xi_{jt}$$

(3)

be the mean utility of car $j$ and $-\alpha_i p_{jt} + \epsilon_{ijt}$ be an individual-specific utility component that depends on price, $p_{jt}$, and on a random term $\epsilon_{ijt}$. The flexibility of the demand model will depend on how the individual specific utility component is parametrized. The price parameter is specified as

$$\alpha_i = \frac{\alpha}{y_i}$$

where $y_i$ is the income of consumer $i$. Assume that in any given year each consumer $i$ receives a draw $\epsilon_i$ which is a vector containing a draw $\epsilon_{ij}$ for each car and also containing a draw $\epsilon_{i0}$ for the outside option of not buying a car. The draws $\epsilon_i$ are i.i.d across buyers but for a given buyer $\epsilon_{ij}$ is allowed to be correlated with $\epsilon_{ir}$ and this correlation is modeled by assuming that $\epsilon_i$ follows the assumptions a two-level nested logit model. Specifically, each market can be partitioned into $G$ different groups and each group $g$ can be partitioned into $H_g$ different sub-groups such that each
sub-group \( hg \) contains \( J_{hg} \) products and the total number of products in the market, \( J \), is equal to 
\[ \sum_{g \in G} \sum_{h \in H_g} J_{hg}. \]
Consumers choose among one of the many cars available (define \( C \) as the set of all cars offered) or the outside option of not buying a car (previously defined as choice 0):

\[ c_i = \arg \max_{j \in C \cup \{0\}} u_{ij} \tag{4} \]

Without loss of generality, normalize the conditional indirect utility of the outside option to be \( u_{i0} = \epsilon_{i0} \). Integrating out the two-level nested logit shocks, we obtain the probability of each consumer \( i \) buying car \( j \):

\[ s_{ij} = \exp \left( \frac{(\delta_j - \alpha_i p_j)/(1 - \rho_{hg})}{1 - \rho_{hg}} \right) \times \frac{\exp \left( I_{ihg}/(1 - \rho_{hg}) \right)}{\exp \left( I_{ihg}/(1 - \rho_g) \right)} \times \frac{\exp \left( I_{ig}/(1 - \rho_g) \right)}{\exp \left( I_i \right)} \tag{5} \]

Following McFadden (1978), \( I_{ij} \) and \( I_i \) are the inclusive values and they are defined as:

\[ I_{ihg} = (1 - \rho_{hg}) \log \sum_{j=1}^{J_{hg}} \exp \left( (\delta_j - \alpha_i p_j)/(1 - \rho_{hg}) \right) \]

\[ I_{ig} = (1 - \rho_g) \log \sum_{h=1}^{H_g} \exp \left( I_{ihg}/(1 - \rho_g) \right) \]

\[ I_i = \log \sum_{g=1}^{G} \exp \left( I_{ig} \right) \]

The predicted aggregate market share of car \( j \) is obtained by integrating over the empirical income distribution:

\[ s_j = \int s_{ij} dF(y) \tag{6} \]

Of special interest for the interpretation of the results are the distributional parameters \( \rho_g \) and \( \rho_{hg} \). The first one, \( \rho_g \), captures the substitutability of cars that belong to the same group \( g \) and the second one, \( \rho_{hg} \), captures the substitutability of cars that belong to the same sub-group \( h \). In order for the model to be consistent with random utility maximization the parameters \( \rho_{hg} \) and \( \rho_g \) must satisfy the following restrictions:

\[ 1 \geq \rho_{hg} \geq \rho_g \geq 0 \]

If \( 1 > \rho_{hg} > \rho_g > 0 \) then we have that consumer preferences across products of the same sub-group are more correlated than consumer preferences across products of different sub-groups within the same group. If \( \rho_{hg} = 1 \) then products of the same sub-group are viewed as perfect
substitutes. If $\rho_{hg} = \rho_g$ then the model becomes a one-level nested logit in which the groups $g$ are the relevant nests; if $\rho_{hg} > 0$ and $\rho_g = 0$ then the model is also a one-level nested logit but with the sub-group as the relevant nest. Lastly, if $\rho_{hg} = \rho_g = 0$ then the model becomes the standard logit model.

With the demand model specified the next step is to define the groups (“top” of the nesting structure) and sub-groups (“bottom” of the nesting structure). Based on the structure of the data and in order to allow for correlation in the consumer idiosyncratic shocks between trims of the same model, the vehicle model (e.g. Honda Civic, Toyota Corolla, VW Jetta) is a natural candidate to be one of the nests. Moreover, considering the question at hand, the safety variable is the other natural candidate to be a nesting variable. The caveat is that despite having two clear candidates for the nesting variables, Economic theory has nothing to say about which one should be the group and which one should be the sub-group and both structures are reasonable a priori. To overcome this issue, I will follow a data oriented approach. The idea will be to estimate the model using the two possible ordering of the nests - model on top, safety on bottom and safety on top; model on bottom – and then test if the model restrictions on $\rho_{hg}$ and $\rho_g$ are satisfied.

### Supply

In any given year $t$ there are $f$ firms. Firms (e.g. Honda) produce cars. As before, a car $j$ is defined as a model/trim (e.g. Honda Civic EX, Honda Civic LX) and is modeled as a bundle of attributes. Define $J_f$ to be the set of cars produced by firm $f$. Moreover, to ease the notation I will omit the subscript $t$.

The marginal cost of each car $j$, produced by each firm $f$ is constant, but vary across cars $j$. Firms choose the wholesale prices of their products $p^w_f = (p_j, j \in J_f)$ in order to maximize their profits:

$$\pi_f = \sum_{j \in J_f} (p^w_j - mc_j) \times s_j(p)$$  \hspace{1cm} (7)

From equation 7 note that there is a distinction between the price firms choose ($p^w$ - wholesale price) and the price consumers pay ($p$ - retail price). This difference is due to the tax structure in the Brazilian automobile market and given a tax rate $\tau$ the link between the firms choice variable $p^w_f$ and the retail price $p_j$ is given by:

---

17The main justification for allowing shocks at the model/trim level is that any competing model would generate substitution patterns that are even more strict than then ones generated by the two-level nested logit. For example, the main competing modeling alternative would be to follow the hybrid model proposed by Song (2015) and assume that the logit shocks are at the model level and then use the vertical structure of the trims within a model. The problem here is that similar to Bresnahan (1987), we will have that non-neighboring trims of the same model will not be substitutes for each other, i.e, the cross-partial derivatives are zero which is an implication at odds with reality.
\[ p_j = (1 + \tau) p_j^w \]

The equilibrium prices are the outcome of a non-cooperative Bertrand-Nash game among the competing automakers and can be found as the solution of the system composed by firms first order conditions:

\[ s_j(p) + \sum_{r \in J_f} (p^w_r - mc_r) \frac{\partial s_r(p)}{\partial p^w_j} = 0 \quad \forall j \]

(8)

The first order condition for each product can be rewritten in a way that relates the wholesale price of a car to its marginal cost and markup:

\[ p^w_j = mc_j + \frac{\Delta^{-1}s_j(p)}{\text{markup}} \]

(9)

where

\[ \Delta_{j,r} = \begin{cases} \frac{\partial s_r(p)}{\partial p_j} \times \frac{\partial p_j}{\partial p^w_j} & \text{if } j, r \in J_f \\ 0 & \text{otherwise}. \end{cases} \]

In order to take the model to the data I assume that marginal costs have the following functional form:

\[ mc_j = W_j \theta + \omega_m + \omega_j \]

where \( W_j \) is a set of car attributes, \( \omega_m \) is a time invariant unobserved cost component that is common among trims of the same model (m) and \( \omega_j \) is an idiosyncratic car specific cost component.

Lastly, I specify how the marginal cost heterogeneity is taken into account in the model. The demand model together with additional structure in the marginal cost function allow me to take equation 9 to the data and thus recover marginal costs. and depends only the model/trim observed attributes \( W_j \) and model/trim unobserved cost shocks \( \omega_j \). Note that this assumption rules out any economy of scope within a model and between models of the same firm. Specifically, the impact of safety equipment into the marginal cost of car \( j \) does not depend on the fact that some other trim of the same model (e.g \( j' \)) might also have safety equipment.
4 Econometric Model

Implementation

We outline here the procedure used to recover the demand and cost parameters. We follow the insights of Berry (1994); Berry et al. (1995) and construct a GMM estimator based on moments generated by interacting the structural demand errors, \( \xi_j \), and supply errors, \( \omega_j \), with a set of instruments. The supply and demand model can be estimated jointly or separately. We chose to estimate them separately, and the main argument for this is to avoid any possible misspecification of the supply side of the model to be carried through to the demand estimates. However, we do so at the expense of a possible efficiency loss.

First, let’s consider the estimation of the demand parameters which are defined to be \( \theta_d = (\beta, \alpha, \rho_{hg}, \rho_g) \). Following Berry et al. (1995) we have that for any guess of the parameters \( \alpha, \rho_{hg}, \rho_g \) we can invert the demand system given by equation 6. Since there is no closed form solution for this integral we rely upon simulation techniques and use 500 Halton draws to approximate the integral. Moreover, the inversion is performed using a contraction mapping similar to Grigolon and Verboven (2014) and considering a convergence criterion of 1e-14. Based on the definition of the mean utility \( \delta \) we construct the sample analogue of the structural demand error for each car \( j \):

\[
\xi_{jt}(\theta_d) = \delta_{jt} - X_{jt}\beta
\]

The interaction of the vector \( \xi \) with a set of exogenous instruments \( Z \) generates the following GMM problem:

\[
\min_{\theta_d} \xi(\theta_d)'\Omega\xi(\theta_d)
\]

where \( \Omega \) is a weight matrix that is constructed in a 2-step procedure. In the first step the model is estimated assuming homoscedastic errors, i.e \( \Omega = (Z'Z)^{-1} \). With the parameter estimates obtained in the first step we construct estimates of the error term and use them to obtain an estimate of the efficient weight matrix. In the second step, we re-estimate the GMM problem using the efficient weight matrix.

The minimization problem involves a potentially large number of parameters (\( K \)-dimensional vector \( \beta, \alpha, \rho_{hg} \) and \( \rho_g \)). To reduce the computational burden, we rely on the fact that for any guess of \( \alpha, \rho_{hg} \) and \( \rho_g \) the \( K \)-dimensional vector \( \beta \) enters the moment conditions on a linear fashion and hence they can be recovered with the following equation:
\[
\hat{\beta} = (X'ZWZ'X)^{-1}X'ZWZ'\delta(\alpha, \rho_{hg}, \rho_g)
\]

Lastly, as it was pointed out by Knittel and Metaxoglou (2014); Dube et al. (2012) the GMM problem is highly non-linear and thus it is difficult to find a global solution. To overcome this issue, we solve the equation 10 using 20 different random initial conditions and keep the estimates that generate the smallest value for the objective function. Moreover, the optimization is performed with the state-of-the-art solver KNITRO interior solution.

Now, consider the pricing equation and the estimation of the marginal cost parameters. Note that given the demand estimates, the markup term in equation 9 becomes a known variable. In addition, the structure imposed on the marginal cost functions imply that the pricing equation is linear in the structural supply error and hence the estimation of the pricing equation is straightforward.

**Specification**

In order to take the model to the data, the mean utility term is parametrized to be a linear function of \(\log(DISPLACEMENT_j)\), \(AIR_j\), \(AT_j\), \(SAFETY_j\) and year fixed effects. The variable \(DISPLACEMENT_j\) is the engine displacement in liters and it provides a proxy of engine power. Furthermore, the log function allows for a decreasing marginal valuation of engine power. \(AIR_j\) is a dummy variable that captures the presence of air-conditioning and \(AT_j\) is a dummy variable that captures the presence of automatic transmission. Both variables are included to provide a measure of how comfortable and possibly luxurious the car is. \(SAFETY_j\) is a dummy variable that captures the presence of safety features. Finally, the year fixed effects capture any macroeconomic event that might affect the value of buying a car relative to the outside option. The income draws \(y_{it}\) are simulated from a truncated log-normal distribution. This log-normal distribution is constructed to fit the mean and the Gini coefficient of the true Brazilian income distribution and the truncation is made at the 50th percentile which implies that I will only simulate households that belong to the mid-class or above.\(^\text{18}\) The decision to truncate the income distribution is arbitrary but has a straightforward rationale behind it; Brazil is a low-income country and many households do not have enough income to pay the monthly installment of even the cheapest car in the market.\(^\text{19}\)

In modeling supply, I assume that the marginal cost is a function of \(DISPLACEMENT_{jt}\), \(AIR_{jt}\), \(AT_{jt}\), \(PWRSTRWHEEL_{jt}\), \(SAFETY_{jt}\) and year fixed effects. To capture possible changes in the effect of safety on the marginal cost during the transition period imposed by the

\(^{18}\) The mean of the Brazilian income distribution is obtained from the National Survey of Households (PNAD) and the Gini coefficient is obtained from the World Bank database.

\(^{19}\) In fact, approximately 13 million households are enrolled in *Bolsa Familia* which is a government program that makes direct cash transfers to extremely poor/poor families.
regulation, I add a variable that is defined as $SAFETY_{jt}$ interacted with a dummy that is equal to 0 before the regulation (2005 to 2009) and 1 during the transition period of the regulation (2010 to 2012). Moreover, the marginal cost equation also takes into account car model fixed effects that capture invariant cost attributes common across trims of the same model.

### Identification

Recall that the GMM problem given by equation 10 requires a set of instruments $Z$ with rank greater or equal to the dimensionality of the demand parameter vector $\theta_d = (\beta, \alpha, \rho_{hg}, \rho_g)$. To construct such instruments, we will rely on the commonly used assumption of econometric exogeneity of the observed product space and on the tax structure faced by Brazilian automobiles.

From the demand model in the previous section, for each car $j$ the unobserved attributes can be written as:

$$\tilde{\xi}_{jt} = \xi_{m} + \xi_{jt}$$

where $\xi_m$ is a fixed effect that captures time invariant attributes that are common among trims of the same model and $\xi_{jt}$ is the residual error term capturing the remaining unobserved characteristics varying across cars and years.\(^{20}\) Defining $X_t$ to be a matrix containing the observed attributes of every car in a year $t$, with the exception of prices, the econometric exogeneity assumption can be stated as:

$$E[\xi_{jt} | X_t, \forall t] = 0$$ (11)

Given the conditional moment restriction (CMR) in equation 11 we have that the unobserved residual error of each car is uncorrelated with observed attributes of every car, in every year, after we condition on car model fixed effects. This assumption is stronger than the one made in Berry et al. (1995) but it is the same made in Grigolon et al. (2017) and it is required so we can use a within transformation of the data. It establishes that the characteristics do not respond to the unobserved demand shocks, which in the automobile industry seems reasonable in the short term.\(^{21}\) Moreover, it also assumes that the serial correlation is absorbed by the car model fixed effect and thus characteristics are do not respond to previous $\xi_{jt}$.

The first implication of the CMR is that we can use variation within model and over time in $\log(DISPLACEMENT_j)$, $AIR_j$, $AT_j$ and $SAFETY_j$ to identify the coefficients that enter the mean utility. Second, based on the CMR and using the insights of Bresnahan et al. (1997); Gandhi\(^{20}\)In estimating the model I do not estimate the car model fixed effects directly. Instead, I use a within transformation of the data.

\(^{21}\)Redesigns and changes of packages/versions are costly and hence they take some time to happen.
and Houde (2016) we can construct instruments that measure proximity in the product space. For any car \( j \) these instruments are: (i) number of trims of the model to which \( j \) belongs; (ii) number of trims of the model which \( j \) belongs that have the same safety status as \( j \); (iii) number of cars made by rival firms that have the same safety status as \( j \); (iv) number of cars made by rival firms that belong to the same category as \( j \); and (v) number of cars made by the same firm that belong to the same category as \( j \). Instruments (i)-(iii) generate exogenous variation that induce substitution within trims of the same model and within trims that have same safety status and hence they are used to identify the nesting parameters. Instruments (iv) and (v) measure competitiveness in the product space and as such they are used to identify the price sensitivity parameter.

The second set of instruments is generated by the Brazilian tax structure and also help to identify the price coefficient. The intuition behind these instruments is that in Brazil cars face different tax rates according to their engine displacement. These differences induce price discontinuities around the displacement thresholds defined by the tax code and as a result, they provide exogenous price variation at the model/trim level.\(^{22}\) In addition, the government is constantly changing the tax thresholds so we also have variation over time.

The identification of the marginal cost parameters follows a similar argument as the identification of the mean utility parameters. In a nutshell, I assume that the supply-side structural errors \( \omega_{jt} \) are mean independent of the car attributes that affect marginal cost after we control for car model fixed effects, i.e.

\[
E[\omega_{jt}|W_t, \forall t] = 0.
\]

With this assumption, the cost parameters are identified by within model and over time variation in \( W \).

5 Estimates

We now turn to the estimates of the demand and supply model. To get some insights on the strength of the instruments I will first present the estimates of the two-level nested logit model without the price random coefficient and the partial F statistics of their first stage. Then, I will move on to the two-level nested logit model with price random coefficient and discuss which nest ordering seems more appropriate. At last, I will present the estimates of the pricing equation and compare them with the estimates of the hedonic regression. This comparison allows us to study how the effect of safety on costs and markups evolve in the sample.

\(^{22}\)The thresholds are: \( \text{displacement} = 1L, \text{displacement} \in (1L, 2L], \text{displacement} > 2L \)

\(^{23}\)As in the demand side we can write the marginal cost shocks as \( \tilde{\omega}_{jt} = \omega_m + \omega_{jt} \) where \( \omega_m \) is a model fixed effect and then assume that \( \omega_{jt} \) is mean independent of the observed attributes that affect marginal costs.
Demand

Table 6 displays the estimates of the two-level nested logit model considering the two possible ordering of the nests. The estimates in column 1 assume that car model is the top nest and the presence of safety is the bottom nest; the estimates in column 2 assume that the presence of safety is the top nest and car model is the bottom nest. First, let’s consider the strength of the instruments. Remember that in the two-level nested logit model we have three endogenous variables: (i) price; (ii) the inside share of \( j \) relative to the bottom nest (\( \log(s_{j|h_g}) \)); and (iii) the inside share of the bottom nest relative to the top nest (\( \log(s_{h|g}) \)). Hence instead of looking for individual F-tests in each equation first stage we need to consider the partial F-test proposed in Sanderson and Windmeijer (2016). Fortunately, for both specifications and for all of the three endogenous variables the first stages satisfy the rule of thumb used to check the strength of the instruments. Obviously, the full model with price random coefficient generates a non-linear GMM problem and as such the linear weak IV test provided here is not directly applicable. However, it is reassuring to learn that the instruments used to estimate the Econometric model have some traction on the relevant substitution patterns in a simplified version of the demand model at hand.

Table 6: Two-level nested logit demand estimates.

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<td>(T)Safety/(B)Model</td>
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</tr>
<tr>
<td></td>
<td>(0.18)</td>
<td>(0.084)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Price</td>
<td>-0.086</td>
<td>-0.089</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.028)</td>
<td>(0.013)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \rho_{hg} )</td>
<td>0.719</td>
<td>0.855</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.054)</td>
<td>(0.024)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \rho_{g} )</td>
<td>0.569</td>
<td>0.725</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.103)</td>
<td>(0.041)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>N</td>
<td>1526</td>
<td></td>
<td>1526</td>
<td></td>
</tr>
<tr>
<td>J-stat</td>
<td>53.66</td>
<td></td>
<td>89.85</td>
<td></td>
</tr>
</tbody>
</table>

F-stat(1st stage)

| Price | 35.23 | 54.83 |
| lsj_sm | 28.14 | 28.67 |
| lss_m | 67.56 | 49.31 |

Notes: Robust standard errors in parenthesis. (T) indicates the Top nest and (B) indicates the bottom nest.

Second, consider the estimates of the segmentation parameters \( \rho_{hg} \) and \( \rho_{g} \). Note that independently of the nest ordering we consider, the magnitudes of the estimates are consistent with
the theoretical assumptions of random utility maximization, i.e \( \rho_{hg} \geq \rho_g \). In fact, we were able to reject the hypothesis \( H_0 : \rho_{hg} = \rho_g \) for both specifications (t-statistic of 2.02 for the specification in column (1) and 4.55 for the specification in column (2)). Thus, we cannot use the estimated patterns in \( \rho_{hg} \) and \( \rho_g \) to make any statement about what should be the nesting order. In this case, based on the J-statistic, the demand model with car model as top nest and safety as bottom nest seems to have a better fit than the demand model with the reverse nesting order.

Table 7 displays the estimates of the two-level nested logit model with price random coefficient. As before, the estimates were obtained considering the two possible ordering of the nests. Columns 1 and 2 display the results of the demand model with the top nest being car model and bottom nest being the presence of safety. The difference between the models in each column is that in column 1 the coefficient on safety is estimated to be constant and in column 2 it is allowed to vary in the regulation transition period (2010-2012) relative to the period before the regulation. Columns 3 and 4 display analogous estimates for the specification in which the top nest is defined by the presence of safety and the bottom nest is the car model. Consider the estimates of the mean utility coefficients. For every model specification, the estimates have the expected sign (positive). AT and AIR are significant for every specification while SAFETY is not significant in the specification in column (1) but it is significant in the other specifications. Lastly, log(DISPLACEMENT) is in general estimated quite imprecisely.

The next relevant set of parameters are the \( \rho_{hg} \) and \( \rho_g \) that capture market segmentation. The first thing to note is that like in the simple model without price random coefficient, the estimates presented in every column satisfy the restrictions imposed by random utility maximization and in every case, we reject the null hypothesis that \( \rho_{hg} = \rho_g \) (t-statistics of 1.8, 1.68, 4.8 and 4.33, respectively). Therefore, the choice of the nesting order should not rely on implied violations of random utility maximization by the estimated model. In this case, the most intuitive criterion in which we can compare the models is the J-statistic. Once more, the demand specification with car model as top nest and presence of safety as bottom nest has a better fit than the demand specification in which the presence of safety is the top nest and the car model is the bottom nest. Further evidence favoring the specification with car model as top nest and presence of safety as bottom nest is that the addition of the variable SAFETY\_After has a small impact on the estimates (column 1 vs column 2). On the other hand, the estimates of the specification with safety as top nest and car model as bottom nest change completely with the addition of the variable SAFETY\_After (column 3 vs column 4).
The estimates suggest that the demand specification with car model as the top nest and presence of safety as the bottom nest is the most appropriate one. So now let’s use the estimates of this specification, the estimates in column 2 to be more specific, as our benchmark model. To have a better grasp of the demand estimates and its implications to the supply side, table 8 displays descriptive statistics of the elasticities generated by the model and markups. The model predicts an elastic demand for every car in the sample which in practice will imply positive marginal costs. Regarding the cross-partial elasticities, note that the elasticity of trims of the same car that have the same safety status (column 2) are approximately twice as large as the elasticity of trims that do not have the same safety status (column 4). This result indicates that within trims of the same model, the presence of safety equipment is a relevant measure of segmentation and possibly an important feature in which firms can induce second degree price discrimination.

The markup estimates are on par with the ones obtained in Berry et al. (1995); Petrin (2002) for the American automobile industry during the 1980s and early 1990s but substantially higher than the ones obtained by Cosar et al. (2015) for the Brazilian automobile industry in the late 2000s. One possible explanation for this discrepancy is that since Cosar et al. (2015) uses the whole income distribution to draw consumers while I truncate the income distribution and use draws from above the median (middle class and above), my demand estimates are less elastic and the markups estimates are higher. Moreover, we could also make the point that their estimates are the ones which are further from the truth. First, as they pointed out, Brazil is the most concentrated market in their sample (C5 of 0.81) and the most closed to foreign competition and
hence the lowest income might be compensated by the lack of competition. Moreover, from 2005 to 2010, the nominal (real) interest rate in Brazil oscillated from 8.75% to 18% (5% to 13%) per year. In such an economic environment one might argue that firms would not be willing to take the risk of producing and selling cars for an average margin of 8%.

Table 8: Elasticities and Markup - Benchmark model (column 2 - table 7)

<table>
<thead>
<tr>
<th>(1) Own Nests</th>
<th>(2) Both Other model</th>
<th>(3) Same safety Other safety</th>
<th>(4) Same model Other safety</th>
<th>(5) Other model Other safety</th>
<th>(6) Markup (level)</th>
<th>(7) Markup (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Median</td>
<td>10.89</td>
<td>2.29</td>
<td>0.013</td>
<td>1.096</td>
<td>0.011</td>
<td>$8491</td>
</tr>
<tr>
<td>Mean</td>
<td>10.79</td>
<td>2.70</td>
<td>0.013</td>
<td>1.401</td>
<td>0.011</td>
<td>$8495</td>
</tr>
<tr>
<td>10%</td>
<td>6.03</td>
<td>0.93</td>
<td>0.008</td>
<td>0.167</td>
<td>0.005</td>
<td>$6799</td>
</tr>
<tr>
<td>90%</td>
<td>15.21</td>
<td>5.04</td>
<td>0.017</td>
<td>2.873</td>
<td>0.017</td>
<td>$10005</td>
</tr>
</tbody>
</table>

Supply

Table 9 columns 1 to 3 redisplay the estimates of the hedonic regression presented in the data analysis section and columns 4 to 6 display the estimates of the pricing model assuming the two-level nested logit demand specification with car model as top nest and presence of safety as bottom nest (table 7 column 2). Moreover, all of the estimates consider variables in levels so the results should be interpreted in Brazilian currency - reais (R$). Column 1 displays the hedonic regression using the whole sample but allowing the coefficient on safety to change during the transition period of the regulation relative to the period before the regulation. Column 2 displays the estimates of the hedonic regression in the pre-regulation sample and column 3 displays the estimates of the hedonic regression in the transition period established by the regulation (2010 to 2012). As the estimate of the coefficient on \textit{SAFETY\_After} and the comparison between the coefficient on safety in column 2 and 3 make it clear, there is a significant drop in the implicit price for safety. Moreover, since the hedonic regression coefficient is interpreted as a mixture of the effect of the attribute on marginal cost and markup, then the logical conclusion is that at least one of these two variables is going down during the transition period of the regulation.

To disentangle what part of the fall in the safety coefficient in the hedonic regression is due to a reduction in cost and what part is due to a reduction in markups we must have an estimate of the marginal cost function. These estimates are provided in columns 4 to 6 of table 9. Comparing the estimates in column 1 with the estimates in column 4 we have that before the regulation, the presence of safety increased the price of a car in R$ 6506 and the marginal cost in R$ 6085; hence the markup on safety was R$ 421 (approximately 7%). After the regulation, safety increased prices

\footnote{All of the monetary variables in this paper are in R$ of 2010. To have an idea of how much would it be in dollars one should roughly divide by 3.}
in R$ 1979 and marginal costs in R$ 1605; hence the markup on safety after the regulation was R$ 374 (approximately 23%). Estimating more flexible pricing equations that allow the coefficient on every attribute to change according to the sample period does not change the previous conclusion.

In this case, the markup before the regulation was R$ 464 (7%) (column 2 vs column 5) and after the regulation the markup was R$ 241 (18%) (column 3 vs column 6). Furthermore, the estimates on how safety impacts the marginal cost of a car after 2010 are close to the numbers released in the press (R$1000 to R$1500).\(^{25}\)

### Table 9: Hedonic and pricing equation estimates.

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Hedonic</td>
<td>Before</td>
<td>After</td>
<td>Full</td>
<td>Before</td>
<td>After</td>
</tr>
<tr>
<td>SAFETY</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SAFETY</td>
<td>6,506***</td>
<td>7,228***</td>
<td>1,589***</td>
<td>6,085***</td>
<td>6,764***</td>
<td>1,348***</td>
</tr>
<tr>
<td></td>
<td>(633.4)</td>
<td>(862.9)</td>
<td>(403.4)</td>
<td>(599.8)</td>
<td>(826.0)</td>
<td>(361.6)</td>
</tr>
<tr>
<td>SAFETY_After</td>
<td>-4,527***</td>
<td>-4,480***</td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td></td>
<td>(622.0)</td>
<td>(583.8)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>AT</td>
<td>3,806***</td>
<td>5,733***</td>
<td>3,660***</td>
<td>3,513***</td>
<td>5,574***</td>
<td>3,291***</td>
</tr>
<tr>
<td></td>
<td>(419.6)</td>
<td>(913.0)</td>
<td>(411.6)</td>
<td>(392.4)</td>
<td>(862.9)</td>
<td>(378.9)</td>
</tr>
<tr>
<td>AIR</td>
<td>4,563***</td>
<td>5,457***</td>
<td>3,697***</td>
<td>3,982***</td>
<td>4,809***</td>
<td>3,161***</td>
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<tr>
<td></td>
<td>(254.4)</td>
<td>(334.5)</td>
<td>(429.8)</td>
<td>(230.9)</td>
<td>(306.7)</td>
<td>(385.5)</td>
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<tr>
<td>DISPLACEMENT</td>
<td>7,451***</td>
<td>5,250***</td>
<td>6,534***</td>
<td>6,793***</td>
<td>6,915***</td>
<td>5,880***</td>
</tr>
<tr>
<td></td>
<td>(492.3)</td>
<td>(612.3)</td>
<td>(882.3)</td>
<td>(453.6)</td>
<td>(569.7)</td>
<td>(806.5)</td>
</tr>
<tr>
<td>Observations</td>
<td>1,526</td>
<td>860</td>
<td>666</td>
<td>1,526</td>
<td>860</td>
<td>666</td>
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<tr>
<td>R-squared</td>
<td>0.913</td>
<td>0.921</td>
<td>0.919</td>
<td>0.910</td>
<td>0.918</td>
<td>0.916</td>
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<tr>
<td>Year FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Model FE</td>
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<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Robust standard errors in parentheses</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>*** p&lt;0.01, ** p&lt;0.05, * p&lt;0.1</td>
<td></td>
<td></td>
<td></td>
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<td></td>
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</tr>
</tbody>
</table>

### Discussion

All in all, the demand estimates indicate a high substitutability between trims of the same model and this substitutability is increased when we consider trims of the same model that have the same safety status. These results point out the importance of considering the fact that cars are usually offered in many different versions. In addition, the high substitutability across trims of the same model based on their safety status indicates that the presence of safety equipment is an important dimension in which firms can possibly induce 2nd degree price discrimination.

The estimates of the pricing equation indicate that a reduction in costs is the most relevant factor in explaining the stark reduction in the safety coefficient obtained with the hedonic regression. However, with the analysis made so far, we can only state what happened with markups

\(^{25}\)http://g1.globo.com/carros/noticia/2014/01/comeca-valer-obrigatoriedade-de-airbag-e-abs-para-carros-novos.html
(level and percentage) and that the presence of safety is an important segmentation dimension. To make any statement about how safety affects product differentiation and second-degree price discrimination between trims of the same car model we need to perform counter-factual exercises to disentangle both effects. The exercise I have in mind considers a market with \( N \) car models such that each model has two versions/trims (\( 2N \) observations). The first counter-factual computes the equilibrium prices assuming that every model has one version with safety equipment and another version without safety equipment. Moreover, the second counter-factual computes the equilibrium prices assuming that both versions of every model have safety equipment. Comparing the within model markup difference across both counter-factual worlds provide a measure of how important is the second-degree price discrimination. Furthermore, comparing how the average markup on safety varies across each counter-factual will provide us a measure of the competitive effect.

6 Counter-Factual

7 Concluding remarks
References


Barwick, P. J., S. Cao, and S. Li (2016). Local protectionism, market structure, and social welfare: China’s automobile market.


